Master of Science in Computer Science
January 2021

Beam refinement and beam tracking using Machine Learning Techniques in 5G NR RAN

Harshal Patel

Faculty of Computing, Blekinge Institute of Technology, 371 79 Karlskrona, Sweden

This thesis is submitted to the Faculty of Computing at Blekinge Institute of Technology in partial fulfilment of the requirements for the degree of Master of Science in Computer Science. The thesis is equivalent to 20 weeks of full time studies.

The authors declare that they are the sole authors of this thesis and that they have not used any sources other than those listed in the bibliography and identified as references. They further declare that they have not submitted this thesis at any other institution to obtain a degree.

Contact Information:
Author(s):
Harshal Patel
E-mail: hapt18@student.bth.se

University supervisor:
Dr. Hüseyin Kusetogullari
Department of Computer Science,
Blekinge Institute of Technology, Karlskrona, Sweden.

Ericsson supervisors:
Michail Triantafyllidis: michail.triantafyllidis@ericsson.com
Marcus Davidsson: marcus.davidsson@ericsson.com

Faculty of Computing
Blekinge Institute of Technology
SE–371 79 Karlskrona, Sweden

Internet : www.bth.se
Phone : +46 455 38 50 00
Fax : +46 455 38 50 57

Abstract

Growing needs of communication, demands higher data transmission rate in 5G NR. In 3rd generation partnership project (3GPP), frames are used to schedule the data to be transfered between the cellular base station (gNB) and user equipment (UE). These frames are further divided into slots and fixed number of slots are used for uplink and downlink. In downlink, several slots are being utilized for CSI-RS report, containing best narrow beams and its power (RSRP). In this thesis, cell downlink capacity is improved by using supervised learning algorithms. Narrow beam is selected using machine learning, no longer using the scheduled slots in downlink, these slots are further utilized in data transmission, resulting in improved cell capacity.

Supervised learning algorithms namely, Support Vector Machines (SVM), k-Nearest Neighbor (k-NN) and Logistic Regression (LR) are compared, collecting the data using the 5G simulator at Ericsson AB, Lund and training them to classify narrow beams. The SVM algorithm is found to outperform other algorithms with accuracy of 78.5% plus 19.6% of neighbor beam selection. The accuracy of algorithm varies depending on the scenario and the quantity of training data used. Plugging-in the SVM algorithm into the simulator, average throughput of multiple users (2, 5, 10, 20, 30 and 40) is collected varying different user speeds (1m/s, 5m/s and 10m/s) and different SSB intervals (20ms and 40ms). For 40ms SSB interval, 40 users and user speed 10m/s, average gain in throughput is found to be 46.6%. Similarly, for 20ms SSB interval, 30 users and user speed 10m/s, average throughput gain is 21.15%.

Keywords: 5G NR, 3GPP, Beamforming, Supervised learning, Machine learning, SVM and Multi-class classification (MCC).

Acknowledgments

I would like to thank my supervisors Michail Triantafyllidis and Marcus Davidsson for providing me this amazing opportunity of master thesis at Ericsson AB, Lund. They have been very patient and constantly helping me by sharing their knowledge, ideas and motivation. I would like to thank all the people working at Ericsson, who helped me in the thesis including the system management people for their consistent input.

I would like to express my gratitude towards my university supervisor Dr. Hüseyin Kusetogullari for his constant support and patience throughout the research.

Last but not the least, a big thank to my family and friends for supporting me all the time. This would not have been possible without you!

Contents

List of Figures

List of Tables

Nomenclature

3GPP 3rd Generation Partnership Project.

5G NR 5th Generation New Radio.

AoA Angle of Arrival.

BF Beam Forming.

CSI-RS Channel Status Information-Reference Signal.

ftp File Transfer Protocol.

gNB or gNodeB Next Generation Base Station.

kNN k-Nearest Neighbor.

KPIs Key Performing Indicators.

LR Logistic Regression.

MIMO Multiple Input Multiple Output.

ML Machine Learning.

MLE Maximum Likelihood Estimation.

NB Narrow Beam.

RBF Radial Basis Function.

RSRP Reference Signal Received Power.

SLR Systematic Literature Review.

SSB Synchronization Signal Block.

SVM Support Vector Machine.

TA Timing Advance.

TDD Time Division Duplex.

UE User Equipment.

WB Wide Beam.

Chapter 1

Introduction

In this era of rapid development, fast communication is one major factor, which has a significant impact on our daily life. To overcome the communication bridge, high throughput and low latency requirements are in demand moving forward from fourth generation (4G) to fifth generation (5G) [17]. In 5G, the usage of mmWave bandwidth is introduced. Using mmWave frequencies for transmission, requires the usage of beamforming technique to reduce the propagation loss between the transmitter and the receiver. Beamforming is a technique, which permits the channeling of the signal energy in the desired direction, by using antenna arrays, and adding their phase shift constructively in a way that it will increase signal strength [6], thus throughput, for a User Equipment (UE). Considering user mobility, and, in order to achieve a stable connection, beam management technique is required. Basic functions of beam management include beam establishment, beam refinement and beam tracking [6]. The best beam in terms of signal level (RSRP) is selected for each user of the cell, with respect to the transmission conditions and environment.

This thesis mainly focuses on the CSI-RS (Channel Status Information-Reference Signal) reporting of beams to the gNB (base station) when selecting a best serving narrow beam for a UE. CSI-RS is channel state information of reference signal, see section 2.1.1 for detailed information. These reports consume a lot of downlink resources, which we try to reduce by using a sophisticated system.

A self learning system is required which can select an appropriate narrow beam for a UE or set of UEs for data transmission. Hence, machine learning is found to be a perfect solution for the problem. To be specific, a machine learning algorithm which can learn from the baseline behaviour and work similarly in the static environment is required. Therefore, in this thesis, supervised machine learning methods which are SVM, k-NN and Logistic Regression have been explored to resolve the corresponding problem in 5G communication.

1.1 Purpose

The purpose of the thesis is to investigate the use of supervised learning algorithm in selection of a narrow beam for a UE without making narrow beam measurements. The study should highlight the use of machine learning and find significant improvement in total throughput of user(s).

1.2 Problem Statement

The NR 5G wireless communication deals with high speed data transfer using the concept of beamforming. Hence, beam selection plays a vital role in optimizing the transmission and reception. In the current scenario, beam selection is totally based on the CSI-RS report of the beam, meaning that UE connects to the beam having the highest power (RSRP) according to the report. This report is sent to the base station and is considered whenever a narrow beam is selected for a UE. This transfer of report, occupies some scheduling time slots according to Time Division Duplex (TDD) when transfer of data takes place. These slots can also be called as resources. The report occupies some downlink resources which can be further used for data transmission, leading to increase in the total cell throughput. In this thesis, the use of machine learning is proposed, to be able to make smart decision (selection of a narrow beam) based on the data available. The role of report in selecting the narrow beam is transferred to a trained machine learning model which can classify the best narrow beam for a user, based on its location. Hence, not utilizing the report anymore, making some extra room for data transmission.

1.3 Aim and Objectives

The goal of this thesis study is to investigate the usage of machine learning algorithms for optimizing the beam tracking process. Machine learning algorithms can be used to make the beam tracking more intelligent, robust, and less resource-demanding. Different machine learning methods are explored to find the best possible beam for a user, and the performance of the algorithm is then compared with the baseline (3GPP) algorithm to find the most suitable algorithm.

The machine learning algorithms are trained by using as input, the beam selection result of the baseline algorithm. Then, a moving UE is utilized to extract the measurements. Finally, each algorithm is evaluated with respect to the performance of the baseline algorithm. The best performing algorithm is plugged into the Ericsson simulator to select best narrow beam and is used to collect the KPIs. Finally, the gain in total throughput is evaluated for different number of users, moving with different speeds.

1.3.1 Research Questions

RQ1: What factors affect the performance of machine learning algorithms, when finding the most effective beam?

Motivation:This research question is answered by performing a Systematic literature review. Multiple factors are responsible for the performance of an algorithm. Using previous researches to list and figure out most crucial factors in this thesis.

RQ2: Which machine learning algorithm outperforms others to find the most effective beam?

Motivation: This research question is answered by conducting an experiment. Here, three algorithms are considered namely, support vector machines (SVM), k-nearest neighbor (k-NN) and logistic regression (LR). To compare the performance of each algorithm, accuracy is used as a performance metric. The best performing algorithm is integrated into the simulator.

RQ3: How much significant change is being observed in the measurements of spectrum utilization when using machine learning compared to the baseline algorithm?

Motivation: Experiment is conducted to answer this research question. When using machine learning for selecting a narrow beam for the UE, some downlink resources are saved. These resources can be further utilized for data transmission. Improvement in total throughput is evaluated, compared to the baseline algorithm.

1.4 Ethical Aspects

Since, the goal will be to increase the cell capacity, more users will be able to utilize the resources. Thus, it makes the current 3GPP (3rd Generation Partnership Project) measurement-based design more sustainable and future-proof. The experiment is performed in the simulated environment, all the data utilized, is collected from this virtual environment. Hence, no personal information of any kind is used in the thesis.

1.5 Outline

Chapter 1 begins with the introduction by providing the context of the thesis followed by the problem addressed. Aims and objectives are mentioned in a distinct manner. Next, the research questions are presented along with their motivation. Ethical aspects of the experiment are also stated. Chapter 2 contains the background knowledge, covering all the significant concepts of telecommunication and computer science relevant to the study. Chapter 3 discusses the papers related to the study, published in previous years. Chapter 4 presents the methodology used in this thesis to answer the research questions. Chapter 5 shows the results achieved in the research and analyse them to justify these results. Chapter 6 discusses the answers to the research questions in the study. Chapter 7 concludes the results and highlights the research gap for further exploration.

Chapter 2

Technical Background

2.1 Telecommunication

In this section, the wireless communication concepts, which are the basis of our research, will be analyzed and explained.

MIMO: Multiple-input multiple-output (MIMO) is a technique used to exploit a better usage of the communication channel between the transmitter and the receiver, by arranging a set of antennas to serve in a controlled manner to get more throughput [22], and higher spectral efficiency. There are many ways that MIMO systems are utilized. Spatial multiplexing could increase the number of transmission layers between the transmitter and the receiver by exploiting the reflections and time varying characteristics of the channel; this could significantly boost the throughput. Transmitting diversity, or receiving diversity could improve the quality and stability of the communication, by reducing the bit error rate, and increasing the signal quality. Beamforming could be used to focus the energy to a specific direction, increasing the signal quality of the user equipment, and reducing interference in a dense radio network deployment scenario.

mmWave: Millimeter wave frequency spectrum ranges from 30GHz to 300GHz [6]. These high range bands are used in 5G NR, as it provides increased bandwidth, in other words, more capacity hence, fulfilling high data transfer demands. High frequency also implies lower wavelength, meaning this is prone to long distance propagation loss [6]. Also, this works the best when the transmitter and receiver are in line-of-sight. This can be improved using a concept called beamforming.

UE and gNodeB: User Equipment (UE) refers to a mobile user which communicates to Base Station (BS or gNodeB) as shown in 2.1.

Figure 2.1: Illustration of (a) User equipment (b) Base station.

Beamforming: It is a technique used in mmWave to improve the range and power of transmission by channeling the energy into the desired direction instead of just broadcasting the signal in every direction as shown in figure 2.2. This is done by arranging antenna elements in a way such that they undergo constructive interference [17]. Antenna elements are metallic devices that are used to send or receive signal. The phased combination of elements adds up to get a beam in one phase having high energy.

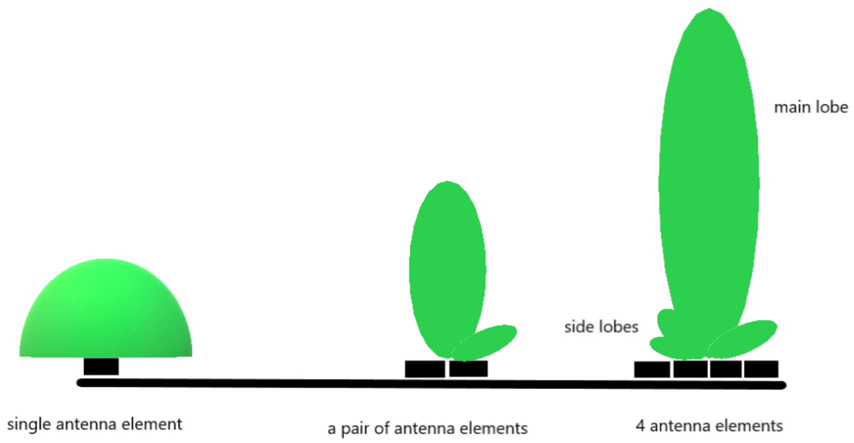

Figure 2.2: Shows radiating elements combining to form a beam like structure along with side lobes formed.

Figure 2.2 illustrates the phenomenon of beamforming, where multiple antenna elements are joined together to form a stronger beam with higher range. Beamforming can be further categorized into analog beamforming (ABF), digital beamforming (DBF) and hybrid beamforming (HBF) [15]. In the context of this thesis, only ABF and only single user beamforming will be considered, meaning that the signal energy is focused towards one user during a transmission, and this is done by adding phase to the transmitted signal before its transmission (no precoding is applied).

- **Wide beam:** Also called SSB (Synchronization Signal Block). These can be referred to as directed blocks of signal, used to establish initial connection to a UE in range (Random Access [15]) as represented in 2.3.

Figure 2.3: Shows conceptual wide beams and UE

- **Narrow beam:** Narrow beams are finely divided beams inside a wide beam, and are used for the data traffic.

Figure 2.4: Shows conceptual narrow beam and UE

- **Angle of Arrival:** Angle of arrival estimation is the process of determining the direction of arrival of signal received by signal processing on an antenna array [5]. This can be calculated by estimating the time difference of arrival between individual elements of antenna array [53] as shown in figure 2.5. AoA can be further used for tracking and localization of the UE. This estimation takes place at gNodeB to estimate the angle of mobile device through uplink channel.

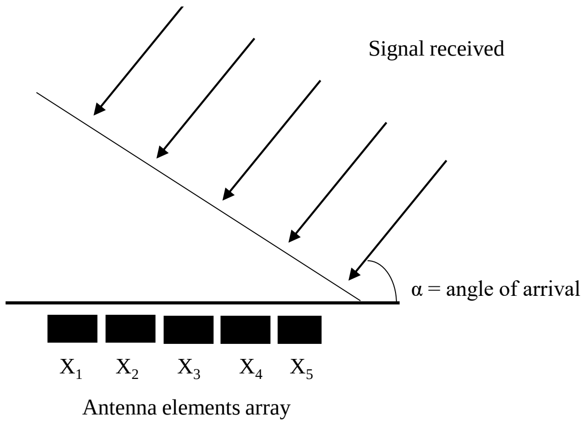

Figure 2.5: Shows signal beams being received at antenna array.

- **Timing advance:** Timing advance is the time that is used to cover the propagation delay by transmitting uplink in advance. Logically, UE that is far from gNodeB exhibit comparatively more timing advance than the one closer to the base station. This is done to make sure that both uplink and downlink subframes are synchronized at gNodeB.

- **Uplink and downlink:** Uplink is the process of data transfer from UE to the base station, and downlink is vice versa as shown in figure 2.6.

Figure 2.6: Shows (a) Uplink (b) Downlink

- **RSRP and RSRQ**
  Reference signal received power (RSRP): is defined as the linear average over the power contributions (in Watt) of the resource elements that carry cell-specific reference signals within the considered measurement frequency bandwidth [17]. Unit of RSRP is decibel milliwatts (dBm). Range of an RSRP is from -140dBm to -40dBm. In general, higher the RSRP value, higher is the strength of signal received. Also, RSRP for a beam is the best experienced in the center of the beam.

Reference signal received quality (RSRQ): RSRQ gives the information about the quality of signal received. The higher the value, the better the signal quality.

- **Beam management:** In analog beamforming, when a beam is formed, only one UE or UEs in the same proximity benefit from that. In case of multiple UEs or mobile UE(s), beam tracking and beam switching is performed. This sophisticated process of beam controlling is called beam management.

- **Beam refinement:** A wide beam is further refined to a narrower set of beams [15]. This process takes place in gNodeB for UE to detect the best one and report it back to the base station.

- **Beam sweep:** Broadcasting directional beams in all the directions is more energy consuming and inefficient, to solve this problem, the concept of beam sweep was introduced. In this, a beam is formed and broadcasted for a time interval at a particular direction, then the direction of the beam is changed after each interval such that it covers all the directions as shown in figure 2.7 Using beam-sweep ensures that the signal can be transmitted with high gain, in narrow beam form to reach the intended coverage area [15].

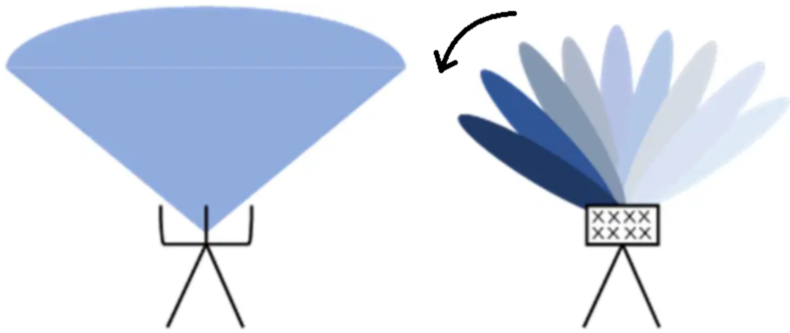

Figure 2.7: Compares the beamforming in sector antenna (left) and MIMO antenna (right). The MIMO antenna undergoes beam sweep to cover the entire range.

- **Back tracking:** For a moving UE, beam switch takes place in vertical as well as horizontal axis to make sure the selected beam is best to get the most throughput. This switch is based on power received on narrow beams.

2.1.1 Channel Estimation

In wireless communications, a channel serves as a medium between a transmitter and a receiver. The channel is subject to various phenomena, such as fading or scattering, and introduces signal power attenuation depending on the position of the user equipment, known as path loss degradation. The unpredictable changes of the channel between the transmitter and the receiver require a mechanism that is called link adaptation in order to establish stable and BLER-free (Block Error Rate - free) communication. Link adaptation ultimately defines the maximum data rate that a communication channel supports. The link adaptation procedure is performed by using channel estimation and channel state information (CSI), reported by UE.

CSI is a mechanism that a UE measures channel properties and reports it back to gNodeB. In order to perform channel estimation, resources are reserved for transmitting pilot sequences [18]. Uplink and downlink both require channel estimation, which is estimated at the receiver in FDD (Frequency Division Duplex) and sent back to the transmitter (gNodeB) [18].

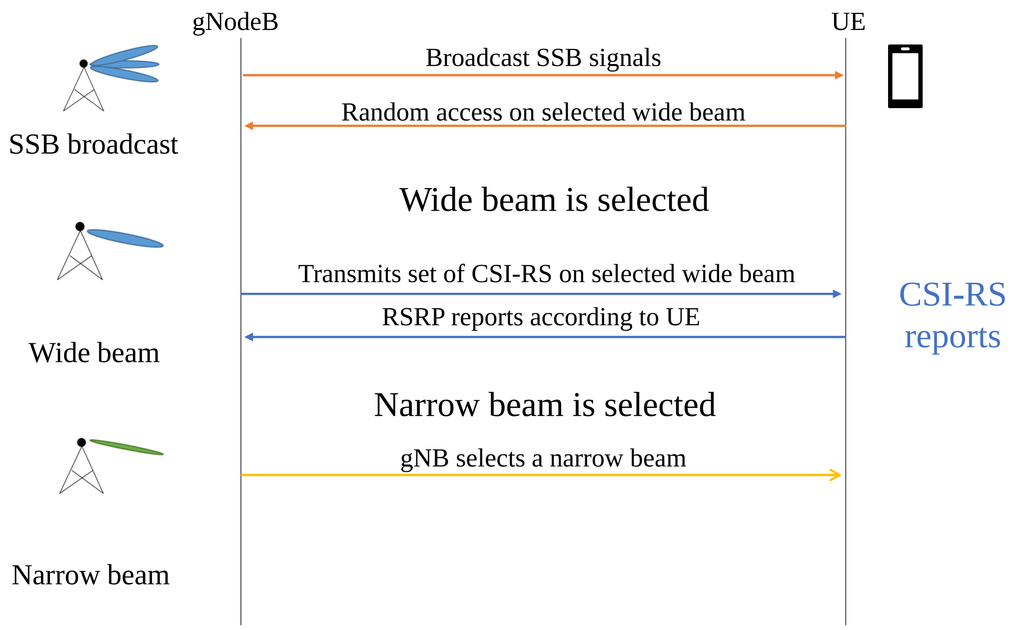

Figure 2.8: Shows the procedure of selecting the narrow beam in baseline.

Firstly, UE selects the best suitable wide beam from the available SSB measurements. Random access procedure now takes place, where UE uses SSB resources to acknowledge the index of SSB selected. This is also known as preamble. Detailed procedure can be found in [38]. Later, gNodeB sends CSI-RS signals to the UE, UE measures on these signals and reports back their strength/quality, based on the report gNodeB selects specific narrow beam for data transfer.

2.1.2 Baseline behaviour

As of now, the baseline algorithm, better known as 3rd Generation Partnership Project (3GPP) tries to select the narrow beam having the highest reported RSRP value. This beam selection is solely based on the best power received on a narrow beam. The UE can be placed at an area, where it can receive beams which belong to the main serving lobe, or beams which are side lobes of other main lobes, which point to other directions, as a result of scattering. This behavior can sometimes turn out to have side lobes as primary beam, which in that position might possess the highest power. At a stationary channel, the best possible beam for a position is ideally the one lying in the middle of a beam. This middle part of a beam is the area of maximum power as compared to the edges of the lobe. Each beam can also have side lobes as secondary lobes, this can be referred to as downside of beamforming. These side lobes are shorter and small in shape as compared to the main lobe. One main lobe can have multiple side lobes depending on the antenna elements used for beamforming.

To make efficient usage of spectrum, transfer of data takes place by using TDD (time-division duplex) transmission scheme. In this technique, the same frequency band is used for uplink as well as downlink. This is done by dividing frames into different time periods called slots. Different slots are allocated for uplink and downlink. These slots are used as overhead resources to manage the traffic. Figure 2.9 shows downlink (DL) and uplink (UL) slots in 3GPP. For each user, downlink as well as uplink resources are consumed for transmission of data. For each user, 2 slots are reserved for CSI-RS report (pink columns) [6]. By utilizing the CSI-RS report, the best narrow beam is selected for each user and is used for transmission of data to the UE. Arrows in the table represent the resources being consumed for each user, i.e. downlink shared channel for CSI-RS measurements and uplink shared channel for indices of best narrow beams measurement report as well as top SSB measurements as per 3GPP. For more details refer [15].

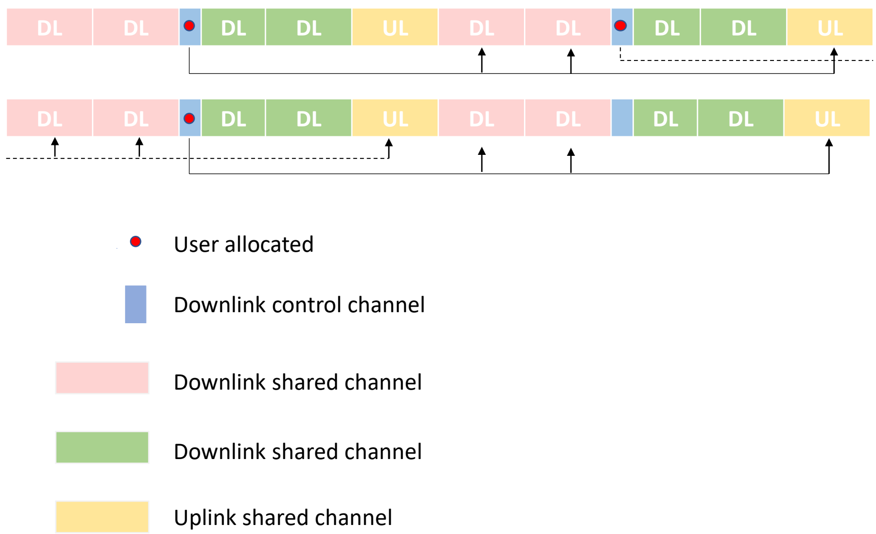

Figure 2.9: Shows 3 users slot allocation in time division pattern for 3GPP.

The consumption of resources (or slots) might seem ignorant for less number of users, but as the number of users increases, the more number of slots are reserved for CSI-RS reporting. Figure 2.11 shows the complete usage of 160 slots time division pattern with maximum number of users (32), each user using 2 slots for narrow beams measurements.

slots	interval (in ms)
160	20
320	40

Table 2.1: Slots and corresponding SSB reporting interval.

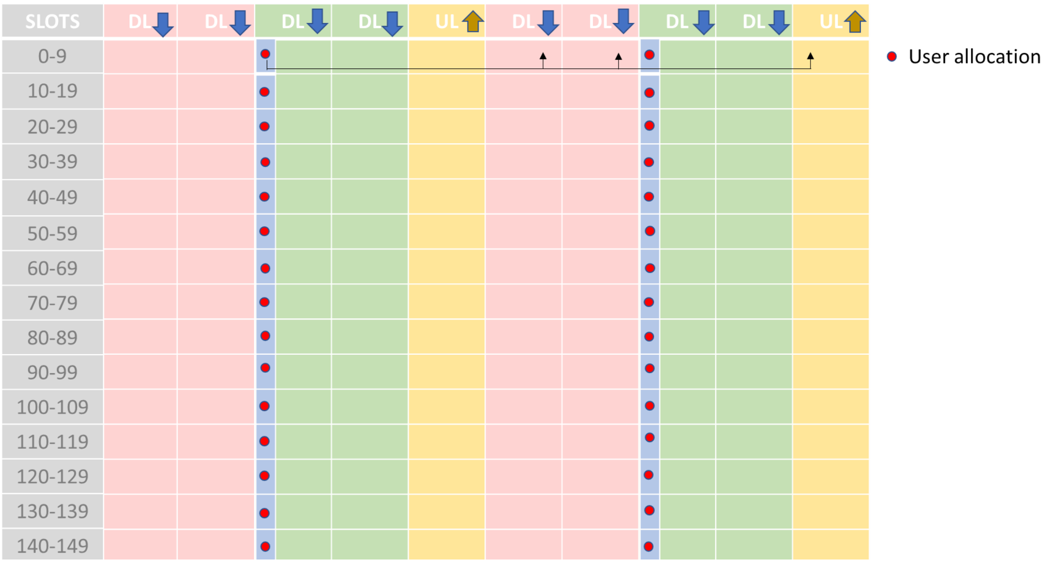

Figure 2.10: Shows maximum user allocation (32) in a 160 slots TDD for 3GPP.

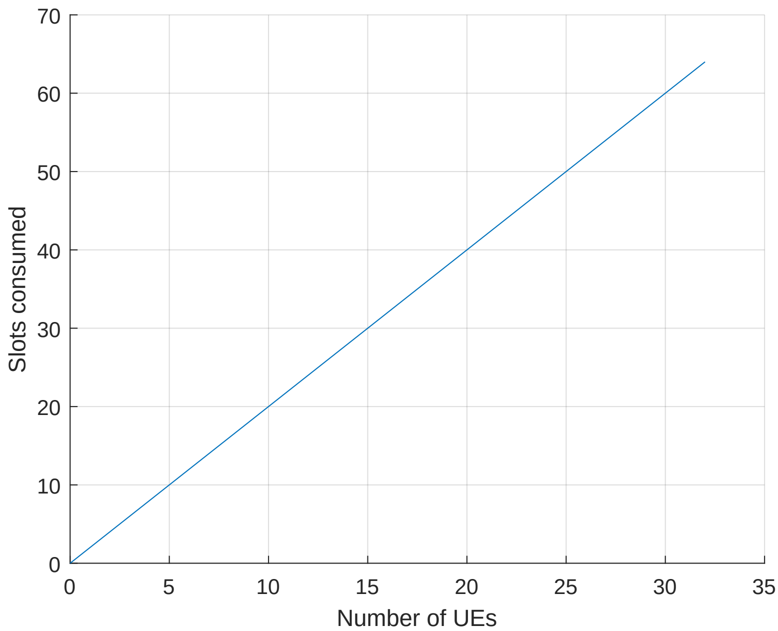

Figure 2.11: Relation between the downlink capacity and number of users.

As the number of users increase the number of downlink slots consumed for CSI-RS reporting also increase linearly, as shown in the Figure **??**. Meaning, a larger number of users when active simultaneously, will require larger reporting. This schedule slot consumption is the problem highlighted in this thesis.

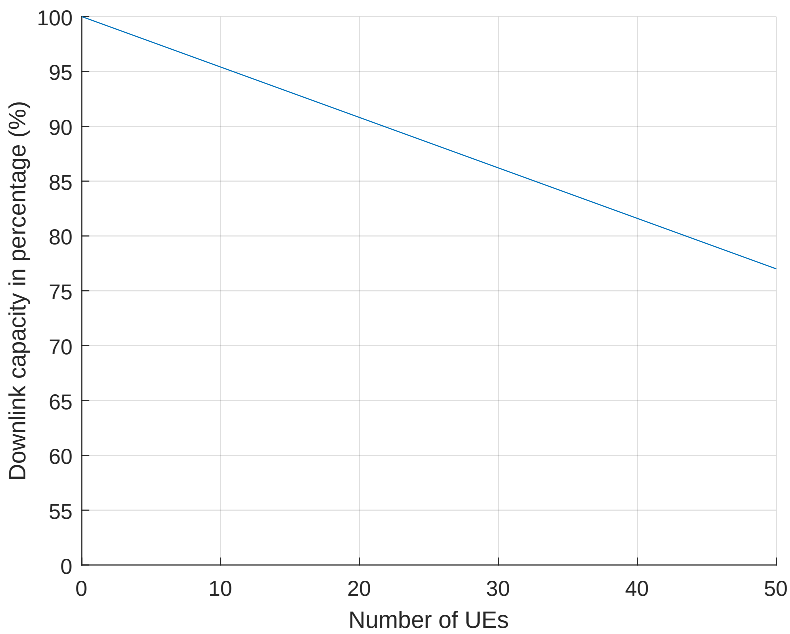

Figure 2.12: Linear relation between slots consumed as the number of users increases.

Figure 2.12 clearly shows that as the number of UEs increase the more number of slots are occupied for CSI-RS reports, hence the decrement in downlink throughput is observed. For less number of users the decrement is not so significant but for 50 users it almost reduces to 50% of total downlink throughput.

2.2 Machine Learning

This chapter begins with introduction to machine learning, later the approaches explored in the thesis are discussed in detail along with the description of parameters used for best performance. However, this study is limited to supervised learning approaches. Discussing the approaches mentioned in a descriptive way to understand their functionality and implementation.

Introduction
Machine learning is an approach used to enhance the working of machines by using historical data to learn, and use this information to make decisions in future. Mainly, it can be divided into 3 categories:

1. **Supervised learning** using known data to train the model by mapping input to output values i.e. instances are given with labels [28].

2. **Unsupervised learning** here output is not known for the model to train i.e. instances are unlabelled [28], but it gradually learns by finding patterns in input data, therefore this approach is not as efficient as supervised learning.

3. **Reinforcement learning (Q-learning)** this approach is used to make smart decisions in an environment where an agent is active and fetches information to the model. State is changed according to action performed and each action is rewarded so as to encourage more positive actions.

Machine learning algorithms explored in this research:

1. **SVM**: support vector machines

2. **KNN**: k-nearest neighbors

3. **LR**: logistic regression

2.2.1 Support vector machines (SVM)

This is the most popular classification technique being used in modern research. Support vector is a supervised learning technique that represents instances as points and creates vectors in space [50]. This helps in forming clusters of different categories or classes and separate them while having the maximum possible gap. This gap or the perpendicular distance between the vectors having closest data points is represented by margin [10].

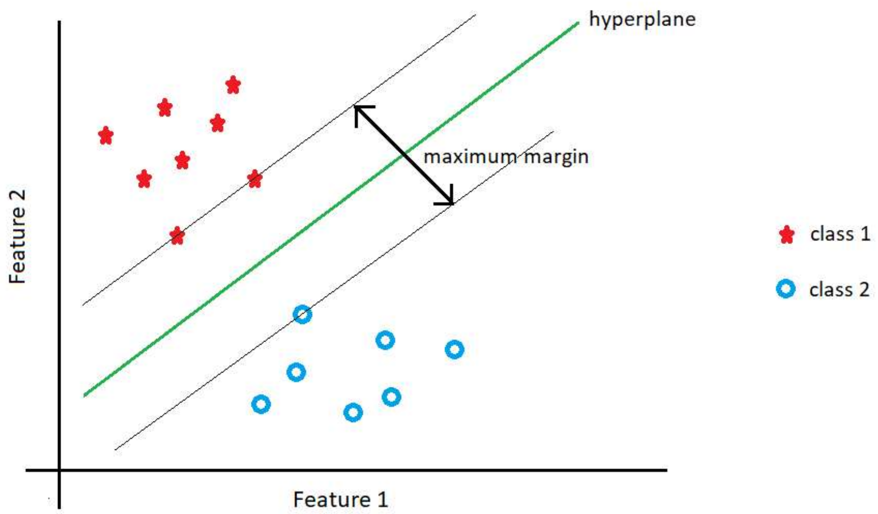

Figure 2.13: Represents an example of linearly separable classification using hyperplane (green line) in linear SVM in a 2D space.

Data points on the margin or boundary of classes are called support vectors. The main motive of the SVM algorithm is to maximize the margin, so that the classes can be classified as wide apart as possible hence, identifying optimal hyperplane. For linearly separable data points, linear hyperplane (or a line in 2D) is enough to do the classification. SVM becomes interesting when the data is linearly inseparable i.e. classes cannot be separated in 2-dimensional space. In this case, kernel function can be used to map data into a higher dimensional space [55]. This additional dimension makes the separation boundary a hyperplane.

Multi-class classification in SVM can be done using two techniques [56]:

- one-against-one (1A1)

  Two classes of data is considered at a time for classification, this reduces the multi-class classification into several binary classification problems. This results in formation of multiple hyperplanes, which can be calculated using the following formula [3].

  $$hyperplanes = \frac{n \times (n-1)}{2}$$

  where, n is the number of unique classes available.

  For classification, each hyperplane votes, the class receiving the highest number of votes is selected to be the final class.

- one-against-all (1AA)

  One class is separated by others at a time in this approach. Hence, n number of classifiers are created in this case [3].

Previous studies have shown that, although the 1A1 method is computationally more expensive compared to 1AA in SVM, the 1A1 method is found to be more practical and stable [24]. Hence, we use 1A1 approach in this research.

Parameters:

- **Regularization function (C)**

  This is also called soft margin cost function or penalizing factor. Higher the value of 'C', the model is less likely to allow misclassifications [10], resulting in lower margin. Thus, one must find a suitable value of C such that margin is maximum and misclassifications are less.

- **Kernel functions**

  Kernel function is used in multi-class classification. It is used to map input data into higher dimensions. In this thesis, since the dimension is more than 2, the l ear function and radial basis function (RBF) were explored; there are other options available for instance, sigmoid function, polynomial kernel or manually customized kernel function [39].

- **Gamma**

  Gamma parameter is only used in RBF. It is basically the measure of how far the effect of each training example reaches with low gamma means far from the hyperplane and vice-versa [49]. Having high gamma value may result in overfitting the model, on the other hand, having too low gamma increases the chances of misclassifications.

2.2.2 Logistic Regression (LR)

It is a statistical model, which is mostly used for binary classification but can be extended for multi-class classification [16]. It uses an 'S' shaped logistic function to find out the probability of a class [18]. It basically uses sigmoid function to find the probability that the class it belongs to. Equation 2.1 shows the sigmoid function used in the logistic regression. Figure 2.14 shows the general equation and the graph of logistic function.

$$f(x) = \frac{L}{1 + e^{-k(x-x_0)}} \tag{2.1}$$

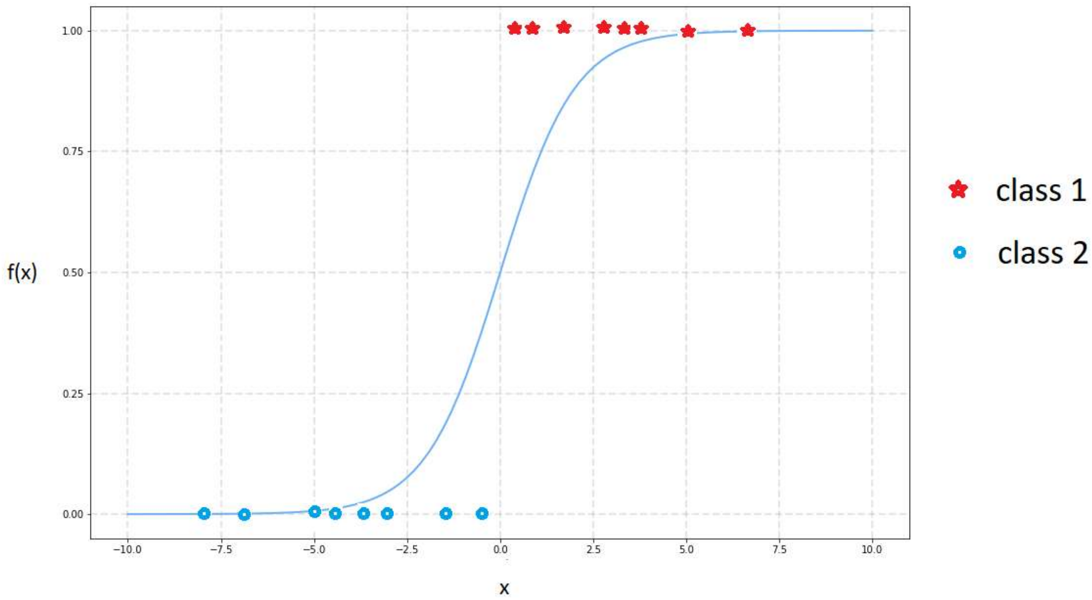

Figure 2.14: Shows classification using sigmoid function graph.

Logistic function essentially helps in categorizing data points in one of the two classes using probabilistic approach. This can be extended for multi-class classification using one of the two schemes 1A1 or 1AA. In case of logistic regression 1AA approach is found to be performing better.

Parameter estimation:

- Least square optimization.
- Maximum likelihood estimation (MLE).

MLE involves finding different parameters for the model in a way that maximizes the likelihood function resulting in better probability of an instance belonging to a particular class using binomial probability distribution. Further information on likelihood function can be found in [23] [36].

In most of the optimization problems, it is preferred to minimize the function rather than maximizing, this negative of log-likelihood function is used. To do so, solvers are introduced in the experiment. Numerous solvers were explored in the experiment namely, 'saga', 'lgfbs', 'liblinear', 'newton-cg' and 'sag'. Basic use of a solver is to find the parameter weights that can minimize the function.

This procedure is repeated for each class present in the dataset and is used for classification of unseen data to find the accuracy.

2.2.3 k-Nearest Neighbor (k-NN)

k-NN is also known as a lazy learning algorithm [54]. K is a positive small number, representing the number of neighbors or training examples in training sample space as shown in the figure 2.15. 'k' training sample data are considered for calculating the distance between data points, new data is categorized based on the classes of neighbors considered. Highest voted category is selected as a class of new data. The optimal value of 'k' highly depends on the type of training data. In general, a lower value of k (1,2,3..) can be a subject to the effects of outliers, resulting in misclassification. On the other hand, having a higher value of k generalizes the classification. Also, selecting too large k value, will result in decrease in accuracy by including the cluster samples not belonging to close vicinity.

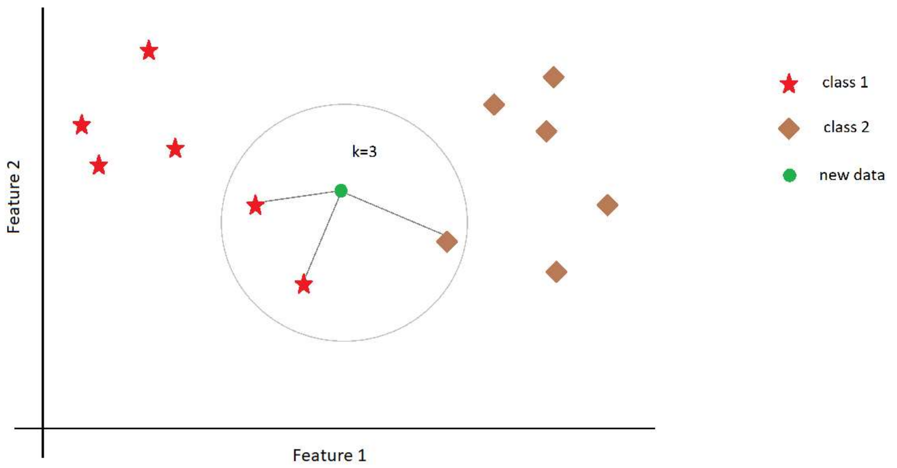

Figure 2.15: Shows 3 neighbors (k=3) considered for classification. New data is classified as class 1.

Parameter:

- In general, 'k' is preferred to be an odd number, to avoid ties between different classes. Calculation of distance between neighbors is computed using minkowski distance [45].

2.2.4 Performance metrics

To evaluate the performance of machine learning algorithms, certain metrics are defined.

- Accuracy: It is defined as the ratio of true outcomes to total number of outcomes. More detailed information on measures can be found in [46].

$$Accuracy = \frac{tp + tn}{tp + tn + fp + fn} \tag{2.2}$$

  True positive (tp): Number of test cases that are predicted as positive and are actually positive.
  False positive (fp): Number of test cases that are predicted as positive, but are negative.
  True negative (tn): Number of test cases that are predicted as negative and are actually negative.
  False negative (fn): Number of test cases that are predicted as negative but are positive.

- Confusion matrix: It gives an idea about the correctly classified and incorrectly classified samples in an experiment. Using confusion matrix is relevant, as it represents the classification of all the classes in that model [33], also it is easy to compare multiple models based on the confusion matrix. Table 2.2 illustrates a confusion matrix.

	Estimated class	
True class	positive	negative
positive	true positive (tp)	false negative (fn)
negative	false positive (fp)	true negative (tn)

Table 2.2: Confusion matrix

- K fold Cross-validation: It is one of the most used performance measure, in which the dataset is validated 'K' number of times by dividing it into K equal parts and finding the average accuracy achieved [17]. The main reason of selecting this technique for the research is that it reduces variance when compared to other estimators. Authors in [40] discuss that various tests performed on different datasets have shown that K=10 is right number of folds for obtaining the best estimate of error. Hence, 10-fold validation is used in this study.

Chapter 3

Related work

This chapter discusses the research done previously in the similar field or field closely related to the study.

In this article [6] authors address similar kind of problem and try to improve the throughput by using reinforcement learning (Q-learning) which includes an agent to perform certain action based on the data collected, this agent is used in a simulator and takes trivial decision while considering cell downlink throughput, error rate, position of UE, direction and speed of moving UE. They clearly present the average increase in downlink throughput in a graphical form for a straight moving UE. This increase is gradual, as the algorithm learns with more data. This algorithm also showed 2% increase in received power when compared to baseline algorithm. Similarly, significant improvement was found in road mover scenario as well, which are evidently represented in graphical form.

In this research [18] authors use four machine learning algorithms namely binary neural network, multi-class neural network, support vector machine and logistic regression techniques are used to classify if the UE is moving (speeds of 30 km/h or 100 km/h) or stationary, in spatial beamforming technology. Amplitude samples are collected and displayed clearly in scatter plots. Results from NN are analyzed using confusion matrix. Finally, neural networks are found to be more accurate. Binary neural network with 98% and multiclass neural network with 89.2% accuracy when the UE is moving or stationary. Further, SVM and logistic regression are implemented to compare with NN and are found to be less accurate, 95% and 93.8% respectively.

In [29] the problem stated is slightly different, authors use DNN (Deep Neural Network) to select one of the two beamforming designs (Maximum Ratio Transmission (MRT) and Zero-forcing (ZF)) in two-user MISO (Multi-input single output) interference channels, based on transmit power and channel vectors. Four vector channels are used, meaning 16 real value features plus transmit power combining to make 17 inputs for input layer. In the hidden layer, ReLU (rectified linear unit) activation function is used to remove gradient. Cross-entropy is used as a cost function to estimate errors. Finally, the model is trained, and accuracy is calculated using different number of samples (10000, 50000 and 1000000) and found to be 77%, 89% and 96% respectively. Also, sum-rate is shown using line graph and achieves more than 99.9% of optimal beamforming combination.

In [17], author tries to optimize the mobility of UE using machine learning, whenever handover or base station switch occurs. The problem addressed is closely related to our study, since the author aims to reduce the power consumption during handovers. If a UE is out of coverage area of a beam, node switch is required, this new node must find the best beam for the UE utilizing minimum power. Problem is narrowed down to two; multiple regression and multiple classification problem. Random forest is used to solve the problem addressed using data collected when 40 UEs are active. Main features considered in the paper are RSRP, position/distance of UEs, speed of moving UEs, timing advance, load on the node and beam indices. The study is conducted in a systematic manner, by performing all the pre-processing required on the data, to be able to input to machine learning algorithm. Beam-hit-rate and difference in RSRP is considered as KPI for the research. 10-fold cross validation is applied to validate the results from random forest algorithm. Finally, RSRP difference was found to be good whereas beam-hit-ratio was found to be worse than expected, concluding RSRP as a feature alone is not enough. The paper gives good insight on features selected and use of supervised learning in this field of area. Random forest was not found very accurate in the study.

In [7], the author addresses to the 5G handover problem similar to [17], but proposes reinforcement learning to find the trade-off between the RSRP value and the power consumed at base station. Plus gain some insights about the useful features. Later, artificial neural network as integrated to it and a hybrid was used to improve the result. Q-learning was not able to predict the best beam RSRP for connection. Author states that improvement was found when RL and ANN were combined. Results are presented in graphical form which makes it easier to understand and analyse. Also, with powerful hardware it is possible to solve handover problem claims the author.

Chapter 4

Method

This chapter explains the methodology used in the research. Started with Systematic literature review to select the relevant algorithm and understand their behaviour, followed by experiment to compare the performance of the algorithms and conclude the results.

4.1 Systematic Literature Review (SLR)

This method is used to gather knowledge and insights from previous studies performed to better understand the behavior of algorithms. A set of papers involving similar areas of study are considered.

The main motive of SLR is to finalize a set of supervised learning approaches that fit the problem addressed in the thesis, and acknowledge the factors that affect their performance. To begin with the research, several supervised learning algorithms were considered, aiming to compare them, and select the best performing algorithm in order to use it in the Ericsson simulator.

Procedure of SLR:

1. Finding and selecting relevant keywords
2. Collecting useful articles and studies
3. Selecting related papers based on inclusion and exclusion criteria
4. Analyzing the results presented
5. Applying the gathered results in the research

Search strings and keywords:

‘supervised learning algorithms’, ‘best performing machine learning algorithms’, ‘comparing machine learning algorithms’, ‘using machine learning algorithms in 5G NR’, ‘3GPP’, ‘beamforming in 5G NR’, ‘Support Vector Machines’, ‘Logistic regression’, ‘k-nearest neighbor’

Articles are shortlisted by identifying their significance and relevance to the topic using digital libraries (IEEE Xplore, Scopus, Springer, etc) and snowballing process.

- ’Supervised machine learning’ AND ’Beam Management’
- ‘Machine learning’ AND ‘5G’

- ‘Machine learning’ AND ‘Parameter tuning algorithms’.
- ’Multi-class classification’ AND ’comparing algorithms’

Inclusion criteria

- Articles published after the year 2005.
- Articles published in English language.
- Articles related to 5G NR or Machine learning.

Exclusion criteria

- Articles published in languages other than English.
- Articles not related to the research.

SLR answers the research question 1 [RQ 1]

- What factors affect the performance of machine learning algorithms, when finding the most effective beam?

4.2 Quality assessment

To make sure that heavy quality of articles is being selected for the research, some specific criteria are considered. Following conditions are considered.

No.	Criteria	Result
1	Does the study involve usage of supervised learning algorithms?	Yes/No
2	Are multiple algorithms implemented and compared in the study?	Yes/No
3	Is the performance of algorithms used in the study justified?	Yes/No
4	What are the benefits and limitations of using these algorithms?	Yes/No
5	How does the performance of algorithms depend on training data?	Yes/No

Table 4.1: Criteria for selecting an article.

Based on the criteria mentioned in table 4.1, an article satisfying 3 or more criteria is considered for the study. SLR is used to sort-list the algorithms to be used and answer RQ1 in the research.

To further investigate the research, the performance of algorithms is evaluated using experiment as methodology. The complete description is stated in section 4.3. In a nutshell, shortlisted machine learning algorithms are trained and tested offline, using the data collected from the 3GPP algorithm. The best performing algorithm is then plugged into the simulator to further evaluate the predicted narrow beam and the throughput gain, when CSI-RS reports are disabled.

4.3 Experiment

Experiment is a quantitative approach which mainly concerns comparing 2 or more groups showing statistical significance that one method is better than the other [14]. Hence, experiment is a suitable methodology for analysing different machine learning algorithms in this research.
Main aims of the experiment are:

- Evaluate the best performing algorithm amongst in offline mode.
- Plug-in the best algorithm in the simulator and test its performance.
- Estimate the increase in total throughput when using machine learning model.

Achieving the aim of the experiment inturn answers the research questions 2 [RQ 2] and 3 [RQ 3]

- Which algorithm outperforms others to find the most effective beam?
- How much significant change is being observed in the measurements of spectrum utilization when using machine learning compared to the baseline algorithm?

Dependent variables	**Independent variables**
Narrow beam (accuracy)	RSRP (power)
Average throughput	Angle of arrival
	Timing advance

Table 4.2: Variables used in the experiemnt.

4.3.1 Tools and libraries

System type	64-bit Operating System
Processor	i5-8350U CPU @ 1.70GHz 1.90GHz
RAM	8GB

Table 4.3: Shows hardware setup.

Library	Description
Pandas	An open source, fast, easy-to-use and efficient library useful for data manipulation (indexing, reshaping, merging, etc) [18].
Numpy	A powerful open source tool, useful for high-level mathematical array operations [19].
Matplotlib	A creative and helpful tool for analyzing and visualizing data by static or interactive plotting [21].
sklearn	An open source machine learning software, featuring various classification and regression algorithms. This library makes utilizing machine learning algorithms extremely simple [12].
Seaborn	A useful graph plotting library, which can also be used for analysing data [20].
LIBSVM	An open source, support vector machines implementation in JAVA. This software can be easily used by converting the input data into a specified format. Documentation provided with the software is extremely simple and easy to understand [13].

Table 4.4: Libraries used along with their description.

4.4 System and Data overview

4.4.1 Simulation

The 5G NR radio network is simulated in Ericsson's internal java based simulation environment, where the UE communicates with the base station (gNodeB) within a hexagonal shaped simulation area, as shown in figure 4.1. The simulation area is 3-dimensional having x, y, and z dimensions. But, to make the experiment simple, only 2-dimensions are considered (i.e. x and y). The base station is located at the coordinates (0, -150), forming beams towards the center of the hexagon. Wide beams (SSBs) are broadcasted all the time, while narrow beam sweep takes place inside a wide beam. There are 12 different wide beams, each wide beam consisting of 12 narrow beams that are distributed in the simulation area as shown in figure 4.3.

Ericsson simulator provides liberty to customize the environment settings, including the movement of the UE, the speed, the number of users, etc. The movement of UE can be changed to the desired mobility pattern by customizing the movement, or by using readily available movement patterns. To be able to replicate the positioning of UE(s), simulation seed is hardcoded. Changing the seed value before the simulation runs, generates different spawning locations or distribution patterns of UE(s) in the simulation area. Keeping the same simulation parameters, simulations were run twice, once with 3GPP algorithm and once with the machine learning algorithm.

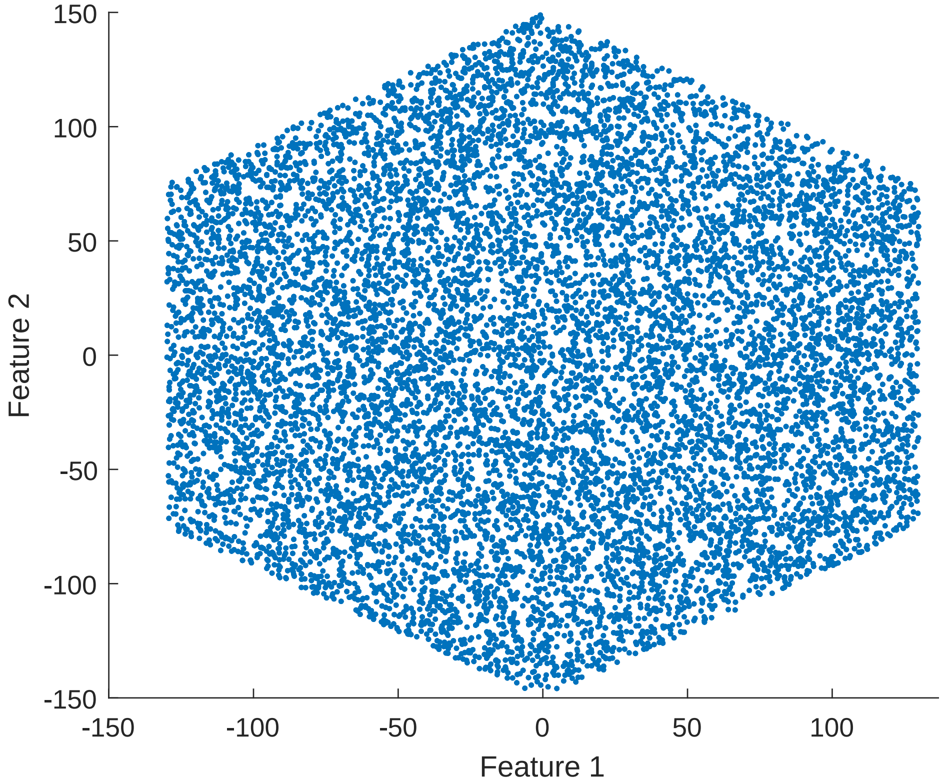

Figure 4.1: Shows UEs distributed in simulation area. The base station is located at (0,-150).

In this thesis, 2 different simulation scenarios are considered. First is when only one UE is simulated at once, used to measure and compare the RSRPs of narrow beams selected by machine learning algorithm as compared to baseline RSRPs and second is when multiple UEs are simulated simultaneously, in order to use machine learning model and calculate the total gain in throughput combined from all the users that are simulated. Simulation setup is divided into two phases, training setup and testing setup. Some standard parameters used for each simulation run shown in table 4.5.

Number of antenna elements	192
Height of antenna	25 meters
line of sight	Yes
Carrier frequency	28 GHz
UE always transmits data	Yes

Table 4.5: Standard configuration for simulation.

Training setup:

In order to collect data for training purpose, same configurations for both single and multiple UE scenario is used in the simulator. During this setup CSI-RS measurements are enabled to make sure that narrow beam indices are available for training the algorithms. Also, various different seeds are used to simulate the distribution pattern of UE(s).

Mobility pattern	Speed	Ftp size	No. of UE(s)	SSB reporting interval
Random spawning, stationary UE	1 m/s	3000	1	40 ms

Table 4.6: Training simulation configuration.

Log items to enable while running the simulation for single UE case:

- SSB RSRPs
- AoA
- TA
- Active narrow beams

Log items to enable while running the simulation for multiple UE case:

- SSB RSRPs
- Active narrow beams

Testing setup:

For testing the machine learning algorithm, an entirely new seed is used inside the simulator for testing the ML algorithm inside same wide beam. Testing setup is further divided into single UE and multiple UE scenario.

Single UE scenario

NB measurements are enabled to be able to compare the RSRP of best narrow beam (3GPP) and the RSRP of narrow beam selected by ML algorithm.

Mobility pattern	Speed	Ftp size	No. of UE(s)	SSB reporting interval
Random spawning, stationary UE	1 m/s	3000	1	40 ms

Table 4.7: Testing simulation configuration for single UE.

Evaluating the performance of the machine learning model by comparing the following KPIs (Key Performance Indicators) collected from the baseline and the machine learning algorithm with same simulation configuration.

- Narrow beam selected
- RSRP of narrow beam selected

Multiple UE scenario

CSI-RS measurement report is disabled and fixed number of UEs are spawned in parallel.

Mobility pattern	Speed (in m/s)	Ftp size	No. of UE(s)	SSB reporting interval (in ms)
Random spawning, stationary UE	1/5/10	MAX	2/5/10/20/30/40	20/40

Table 4.8: Testing simulation configuration for multiple UEs.

Significance of different SSB reporting interval is that for shorter reporting interval, calling of machine learning class will be more frequent, hence narrow beam switch is more frequent and up-to-date.

KPIs for to enable in multiple UE scenario to estimate the performance of machine learning algorithm.

- Downlink throughput of each UE

4.4.2 Data description

To conduct the experiment, the first step is to figure out useful features and labels to train the shortlisted supervised learning algorithms. In the Ericsson 5G simulator, log items that seemed interested for the experiment are listed below.

Features:

- **RSRP:** Each UE in the simulator experiences a certain power of a wide beam called reference signal received power (in dBm), this power depends on the location of UE. Higher power implies that the UE is near to the beam and vice versa. This RSRP experienced by UE is reported to gNodeB for further utilization. Here, wide beam RSRPs are considered as one of the features for machine learning algorithms. There are 12 different wide beams present in the simulator, UE experiences different power for each wide beam, hence 12 different RSRPs. Highest RSRP meaning that the UE is either inside that wide beam or is nearest to it as represented in the figure 4.3 (Note: figure 4.3 shows an illustration of wide beam distribution for understanding purposes only and does not represent wide beams used in real products).

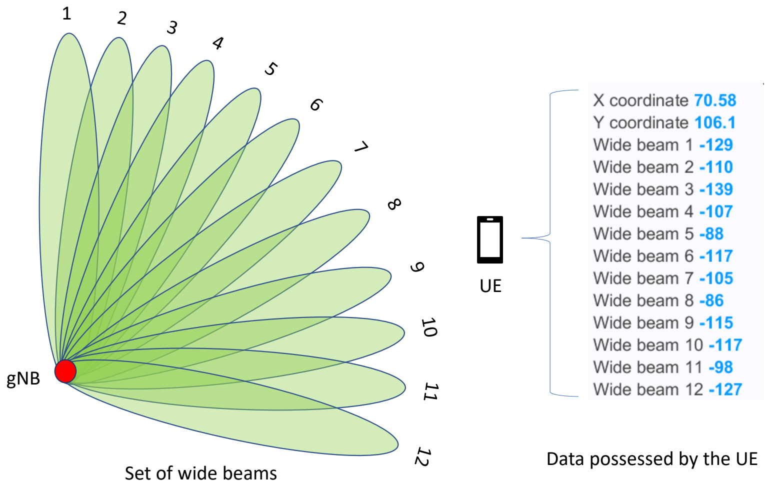

Figure 4.2: Shows conceptual wide beams broadcasted by the gNB and information possessed by the UE.

- **AoA:** Angle of arrival is the angle at which the beam is incident on the antenna array. It is measured by calculating the time difference of arrival between individual elements of array [53]. This feature is indeed helpful in narrowing down the narrow beams up to 2-3 beams for classification. AoA is found to have the best correlation with the narrow beam. For this experiment, to make this data more realistic, a randomness of about 2.5° is added.

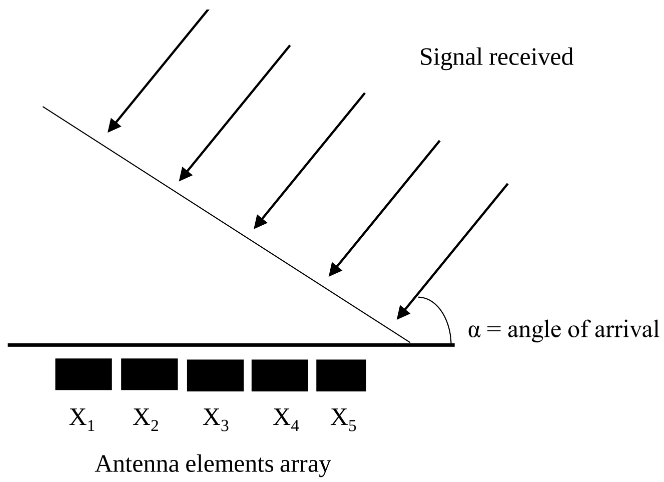

Figure 4.3: Represents the angle of arrival of signal on antenna elements.

- **Timing advance (TA):** It is the adjustment made by the UE based on commands from gNB when establishing the connection. This potentially gives an idea of distance between the UE and the base station. TA is measured in meters. For this experiment, the granularity of TA is 9.8 meters.

Labels:

- **Narrow beam:** A wide beam contains 12 different narrow beams. Each narrow beam is associated with a particular set of features, depending on the narrow beam.

Above stated features and labels are used to train each algorithm and test them offline (i.e. outside the simulator). Tuning the parameters of these algorithms is the most crucial step in the experiment which decides the performance of the algorithm.

4.4.3 Data collection

In this thesis, the investigation is performed inside one single wide beam. Distribution of wide beams in the simulation area is shown in the figure 4.4. Different UEs having specific wide beam active, are color coded and plotted by collecting their x and y coordinates. Wide beam number 8 (shown red in color in figure 4.4) is found to be appropriate as it lies in the center of the simulation area and makes it easy to visualize the narrow beams present inside it. Data samples from inside wide beam 8 are collected using 3GPP algorithm. Multiple seeds are used for collecting the data, as this makes sure that the data collected is uniformly distributed.

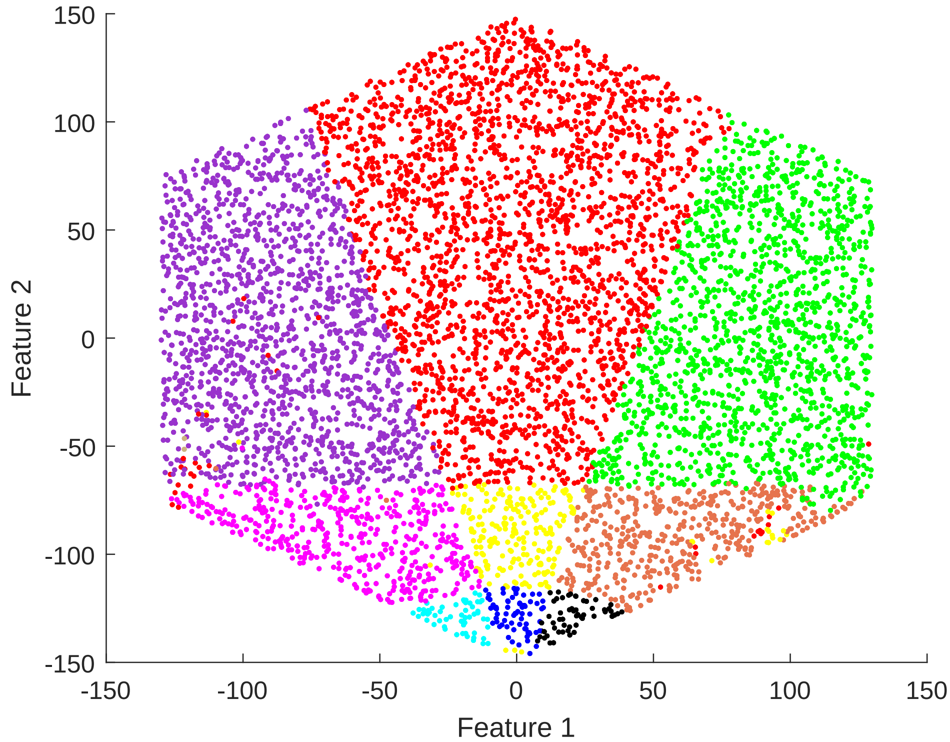

Figure 4.4: Distribution of different wide beams represented using color code in the simulation area.

Movement / spawning of single UE

When collecting the data for training the machine learning algorithms, single UE setup was used where a UE starts to spawn randomly in the simulation area, being active for some time interval (depending on ftp size) and becomes inactive eventually. Soon after the deactivation of the first UE, a new UE is spawned at a random location possessing the enabled logs. The image shown in 4.4 shows the randomly spawning of UE distinguished by the wide beam they belong to. Simulation is run for about 1000 seconds to collect more or less 9,000 samples of UE.

When the CSI-RS measurements are enabled, UE spawns at random positions but only those samples are collected which have wide beam 8 as active beam as shown in figure 4.5. Each UE possesses all 12 SSB measurements, the angle of arrival (AoA), the timing advance (TA) and the active narrow beam. On top of that, logs having coordinates of UEs are also enabled. These coordinates are used for visualizing, by plotting the UEs. Table 4.9 shows the data collected for one UE in the simulator. Similarly, the same is done for each UE.

Log item	**Value**
X-coordinate	70.58
Y-coordinate	106.67
Wide beam 1	-129
Wide beam 2	-110
Wide beam 3	-139
Wide beam 4	-107
Wide beam 5	-88
Wide beam 6	-117
Wide beam 7	-105
Wide beam 8	-86
Wide beam 9	-115
Wide beam 10	-117
Wide beam 11	-98
Wide beam 12	-127
Timing advance	109
Angle of arrival	1.9
Best narrow beam index	11

Table 4.9: Shows data collected for a UE inside wide beam 8 in the simulator.

After the end of simulation, a text file is generated containing all the information about each UE and its corresponding measurements. This information is filtered, and the machine learning models are trained and tested on this data. Models are trained and tested on wide beam 8 only. The best algorithm is plugged into the simulator and tested inside wide beam 8. When a wide beam is active, UEs possessing that wide beam experience the best power as compared to other wide beams, which can be observed in the table 4.9.

The table 4.9 shows the RSRP distribution of a randomly selected UE inside the simulation area when wide beam 8 is active. As seen in the table, UEs located in the wide beam 8 possess relatively higher RSRP compared to the UEs outside the wide beam.

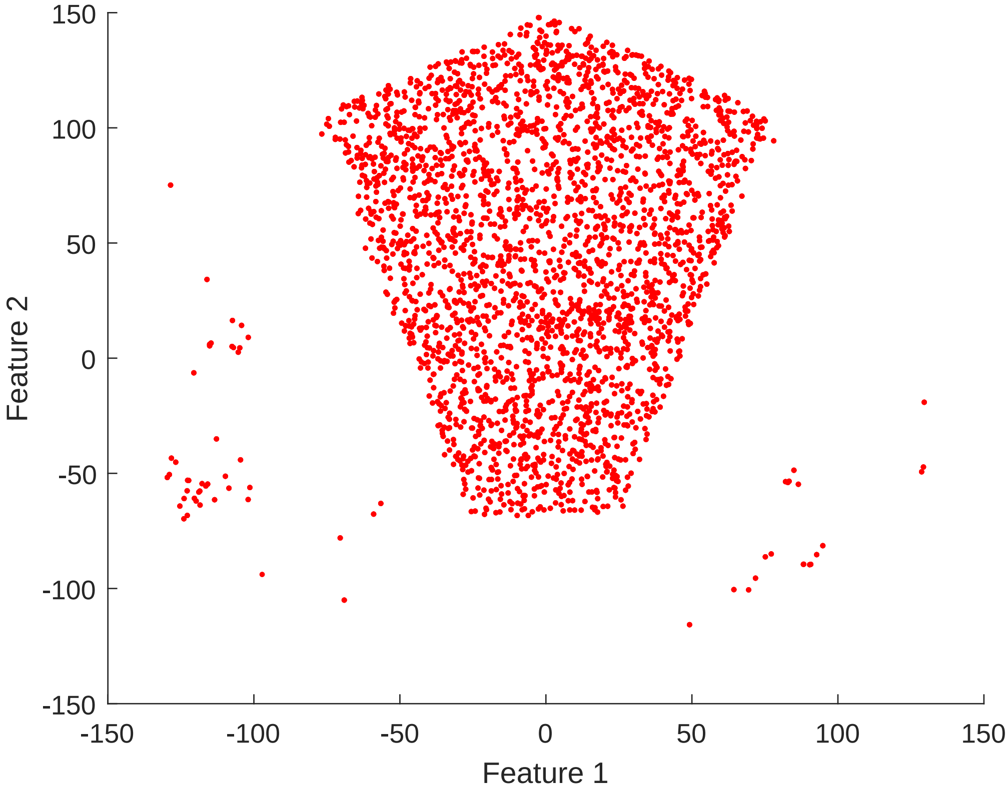

Figure 4.5: Distribution of UEs having wide beam 8 active. Outliers represent UEs connected to side lobes.

Figure 4.5 represents the UEs active inside wide beam 8. Clusters outside the main lobe are the points where side lobes of wide beam 8 are active and possess better power than other beams. Side lobes are selected by the UE when they possess high magnitude of power and have optimal beam for data transmission as compared to other wide beams.

The main purpose of using machine learning is to map the RSRPs, the AoA and the TA to the narrow beams. The presence of side lobes in the training data, might lead to mis-classifications in machine learning algorithms by interfering with the mapping procedure.

4.4.4 Data pre-processing

Text file generated at the end of simulation run contains all the logs enabled for the experiment, depending on the configuration settings as mentioned in section 4.4.1. This file is used to extract useful information, features and labels for training and testing purposes. The raw text is then filtered and converted in a format discussed in [13].

The data generated was quite accurate and complete, no missing values were found in the process of data collection, but in order to make the data more realistic, some randomness was included in the angle of arrival. In high band the granularity in TA is found to be around 9.8 [31] and an error estimate of 2.5 degrees is added to the AoA [32]. Detailed information can be found in the respective articles.

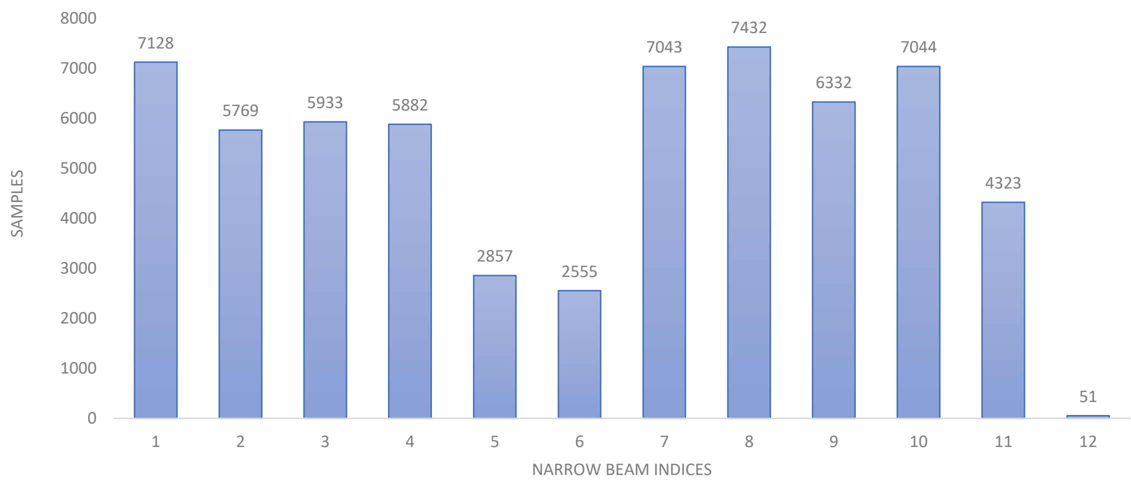

Figure 4.6: Distribution of narrow beam samples collected inside wide beam 8.

All the narrow beams are not used equally inside a wide beam; the distribution of narrow beams inside wide beam 8 is represented in the graph 4.6. Narrow beam 12 is seldomly used, hence limited samples are collected. Authors in [19] mention that if the data available is imbalanced, the class with least instances available can be treated as noise. Authors mention some other methods to deal with imbalanced data like adjusting mis-classification costs, oversampling minority class samples and downsizing majority class samples. These techniques can be used to improve the uniformity in dataset. Ignoring narrow beam 12 class, all the other classes have significant data available for training the models. Eventually, all the models have to be trained such a way that they behave similar to the baseline algorithm. Thus, imbalanced data is used for training the machine learning models i.e. no further addition or removal of samples from any class is done.

More than 60,000 samples from wide beam 8 are collected to train the machine learning algorithms. The process of data collection is done in multiple simulations (more than 15), each time with different seeds to maintain the uniformity in samples collected.

4.4.5 Experimental implementation

This section explains the steps followed to perform the experiment and the idea behind it.

In the beginning of the experiment, algorithms shortlisted from SLR are trained on an over 60,000 sample dataset collected by moving a UE on random positions inside a wide beam 8. This dataset is internally divided into 80% training and 20% testing to achieve best results as stated in [30]. The crucial step is to tune the hyperparameters in such a way that it maximizes the accuracy of narrow beam classification. SVM, LR and kNN are fine tuned to perform best. Comparison is made between the three algorithms to select the one outperforming others.

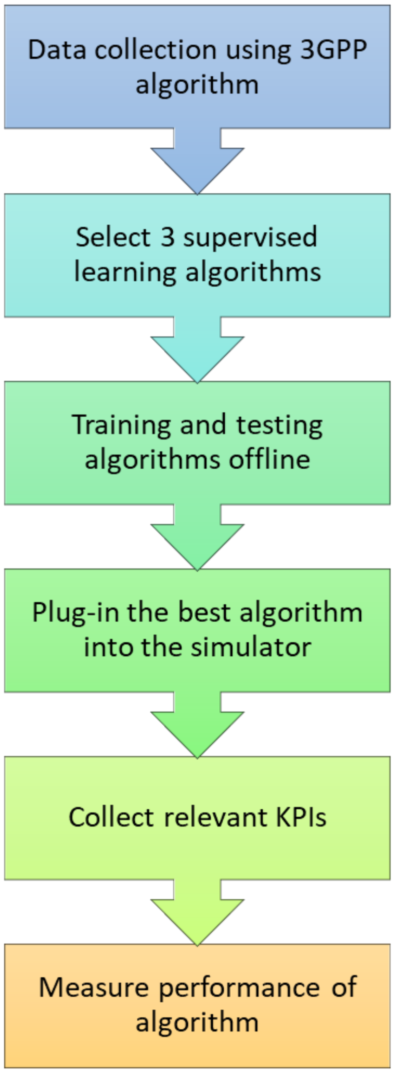

Figure 4.7: Block diagram showing the overview of flow of the experiment.

Mentioned flow in figure 4.7 is explained below step-by-step:

Step 1: Data is collected for training the model, using the baseline algorithm (3GPP) in the simulator.
Step 2: Three best supervised learning algorithms are chosen for comparison.
Step 3: All three algorithms are trained and tested, to find the best algorithm based on accuracy.
Step 4: The best model is imported and plugged into the Ericsson simulator.
Step 5: CSI-RS measurements are disabled and machine learning is enabled to test the performance of model inside the simulator.
Step 6: Performance of machine learning algorithm is evaluated inside the simulator. This model is further used to compare the total throughput gain when machine learning is enabled.

4.4.6 Hyperparameter tuning

Tuning the parameters of a machine learning algorithm is the most crucial step which directly affects the performance of the algorithms [37]. In this experiment, to find the best fit of parameters, various combinations are tried and tested. The best parameters found for each algorithm is mentioned below.

Support vector machines

- regularization parameter : In our experiment, C=2 was found to be the optimal value.

- Kernel function : Linear kernel function was found to classify the best amongst.

- Gamma : Gamma value in the experiment is taken '1/number of features' i.e. 0.067 [13].

k-Nearest Neighbors

- k-value : Several different k values were explored in the range of [1,15] where k=7 was found to be optimal.

Logistic regression

- Maximum Likelihood Estimation (MLE) is used to estimate the best parameters.

- Solver : 'newton-cg' is found to perform best.

4.4.7 Idea behind the experiment

The idea of using machine learning algorithms is to select the best narrow beam, by doing so, it reduces the usage of downlink resources. By using machine learning, CSI-RS measurements are no longer required, resulting in availability of extra slots in downlink channel plus no more narrow beam RSRP reporting in uplink channel.

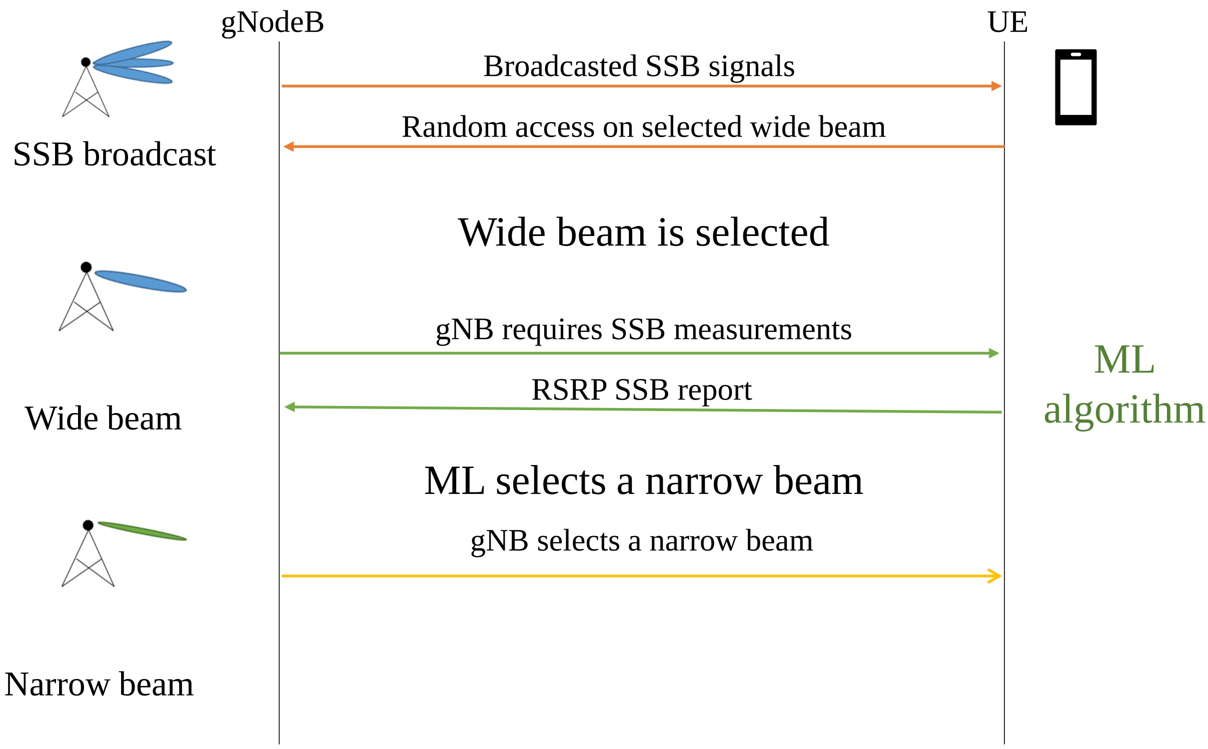

Figure 4.8: Working of SVM to find the best narrow beam after random access.

These freed slots are further used for data transfer. This would eventually result in increment in average throughput for multiple users and reduction in the response time. Average throughput is preferred instead of median, in order to consider the contribution of all the active UEs.

Figure 4.9: Conceptual TDD pattern with no CSI-RS reports.

The figure 4.9 represents the expected time division (TDD) pattern for one user, without CSI-RS measurements when using machine learning. This will result in improving the throughput and reducing the response time for a user.

The use of machine learning in the overall scenario can be shown in the diagram 4.10, where SSB measurements are used along with AoA and TA. These measurements are then fed into the ML model which returns the best narrow beam index as shown in 4.10. This narrow beam is then used for transmission without having CSI-RS reports.

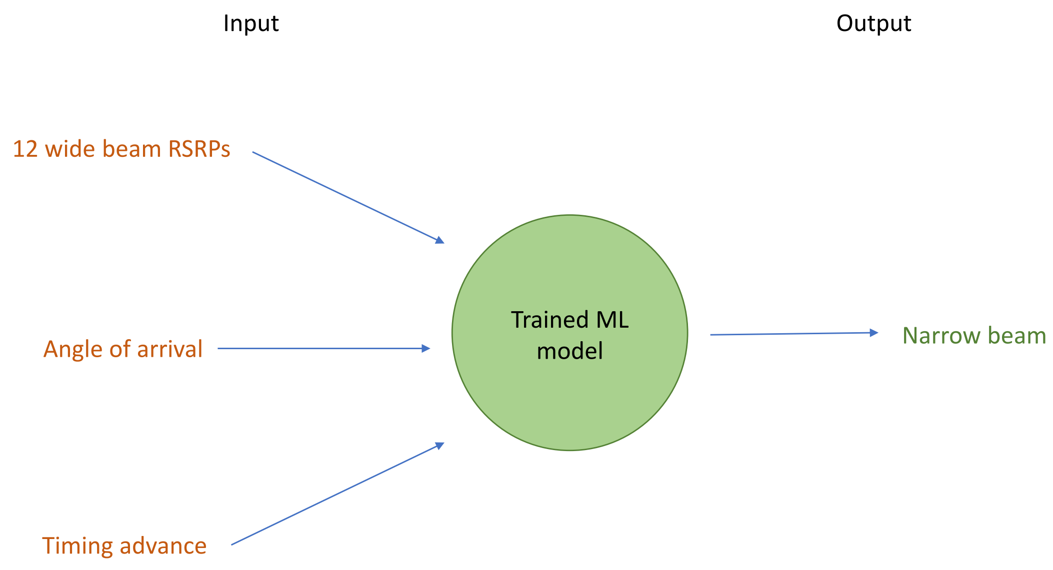

Figure 4.10: Inputs and output of trained ML algorithms for single UE scenario.

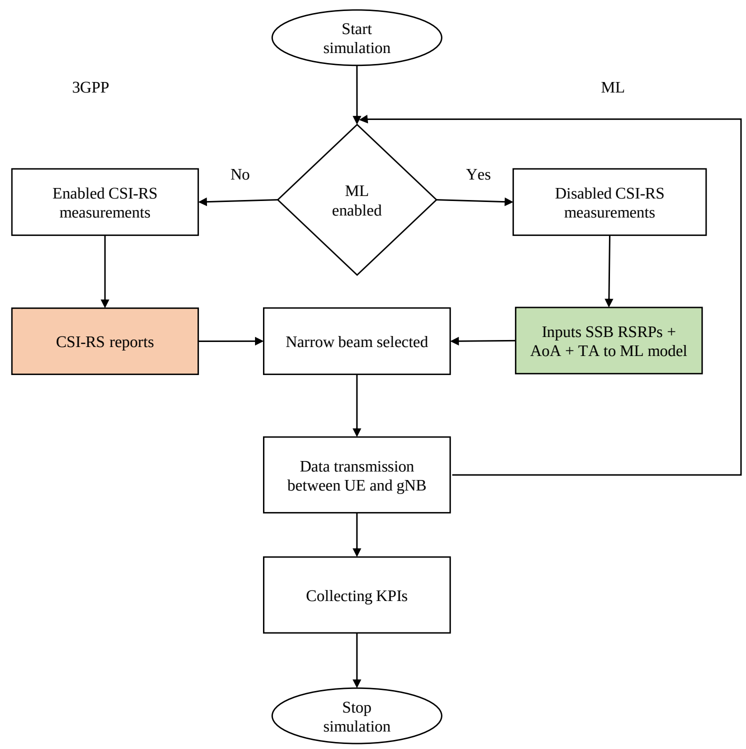

Figure 4.11: Flow of working inside the simulation.

Figure 4.11 shows the flow of simulation. Simulation starts with, checking if the machine learning is enabled or disabled. If enabled, then the CSI-RS measurements for the report are no longer required. The SSB RSRPs, the AoA and the TA measured on wide beams are sent as input to the model which returns the best narrow beam for the user. If machine learning is disabled, measurements on narrow beam is used for CSI-RS report, to select the best narrow beam for the user. This narrow beam is then used for data transmission between the UE and the gNB. After each iteration, KPIs enabled are collected. This process is repeated until the simulation is ended. Finally, the simulation results when machine learning is enabled is compared to when the machine learning is disabled (3GPP).

Model integrated into the simulator is only trained on data collected in wide beam 8, therefore the testing is only done in wide beam 8. However, separate models can be trained for each wide beam and respective models can be used whenever there is a wide beam switch covering the whole simulation area.

Chapter 5

Results

This chapter presents the results received from the SLR and the experiment performed. Results are divided into two sections SLR and Experiment. Each result is followed by their analysis.

5.1 Systematic Literature Review results

No	Article	Results
1	User Equipment Characterization using Machine Learning [18]	This study focuses on use of Neural network, SVM and Logistic Regression to classify the speeds of UEs. The models are trained on binary classes and the accuracies are found to be NN(98%), SVM(95%) and LR(93.8%). NN was also trained on multiple-classes and found to have 89% accurate.
2	Comparison of Random Forest, k-Nearest Neighbor and SVM for Land Cover Classification [48]	The study compares three machine learning algorithms, on image datasets. High accuracy is found in both balanced and imbalanced dataset when the training data for the algorithms was large. It is clearly stated that accuracy of an algorithm is highly dependent on the parameters chosen. Accuracy for SVM(94%), k-NN(94.10%) and RF(94.02%) was found.
3	Link Prediction using Supervised Learning [1]	This paper uses multiclass classification to compare performance of SVM, kNN and decision tree. Also, it explains the effectiveness of the features from their class. SVM is found to outperform all other algorithms.

No	Article	Results
4	Assessment of effects of training data selection on the landslide susceptibility mapping: A comparison between SVM, LR and ANN [25]	This paper compares the performance of SVM, LR and Artificial Neural Network(ANN). Overall accuracies found to be 81.42%, 79.82% and 70.2% respectively. The results also show that accuracy is dependent on sample size of training data. LR was found to be less sensitive to features compared to SVM and ANN.
5	Comparison of the efficiency of Machine Learning algorithms on Twitter Sentiment Analysis of Pathao [41]	The research focuses on comparing SVM, LR and Naive Bayes for binary text classification. Pre-processing and feature extraction is performed to get the accuracy of 82.3%, 75% and 79.3% respectively. The accuracy is dependent on quality of training data used.
6	Early Flood Risk Assessment using Machine Learning: A comparative study of SVM, Q-SVM, KNN and LDA [26]	Comparison between SVM, Quadratic-SVM and Linear discriminant analysis (LDA) classification algorithms is performed in this article. It has been stated that large amount of clean data is required for correct weather forecasting. Accuracy of SVM(97.4%), Q-SVM(96.9%), KNN(91.7%) and LDA(87.1%) was found.
7	Credit card fraud detection using Machine Learning Techniques: A comparative analysis [4]	This paper compares SVM, KNN and LR in binary class classification. Dataset used contains more than 284,000 samples. KNN outperforms all the other algorithms with 98% accuracy. The reason for such high accuracy is that the research has high amount of data for two classes. Performance of algorithm directly depends on quantity of training samples.
8	Supervised Machine Learning Approach for Effective Supplier Classification [21]	This study deals with comparison of supervised learning classification algorithms namely SVM, KNN, Naive Bayes and LR. Accuracies are compared for un-sampled and different data distribution to gain insights. Concluding that KNN shows significant performance of all.
9	Touch Analysis: An Empirical Evaluation of Machine Learning Classification Algorithms on Touch Data [35]	This research is based on touch-screen based analysis using SVM, KNN and Deep neural network. Dataset contains 41 subjects and 30 features. Features play a crucial role in performance of an algorithm. DNN was found to be 100% accurate while SVM and KNN, 96.7% and 94.6% respectively in the study.

No	Article	Results
10	Multiclass and Binary SVM Classification: Implications for Training and Classification Users [34]	Authors in this study extend the use of SVM for multiclass classification. Using one-shot multiclass classification instead of series of binary classification is found to be more accurate. 92% and 90% respectively. Article also discusses the advantages of one-shot multiclass classification.
11	Filter Selection Methods for Multiclass Classification [12]	The study is focused in filter feature selection methods using SVM algorithm. Stating that irrelevant features decrease the performance of machine learning algorithm. CHI is found to have rank best features for a dataset.
11	Identification and authentication for wireless transmission security based on RF-DNA fingerprint [52]	This research paper compares the performance of SVM and LR to multiple discriminant analysis (MDA). Results also show that adding a mean feature improves the accuracy of algorithm. SVM is 94% and LR is 89.2% accurate.
12	Drone Detection and Classification Using Cellular Network: A Machine Learning Approach [44]	The article proposes a suitable set of features for classification using DT, LR, DA and kNN algorithm. The conclusion being, feature selection plays an important role in improving the accuracy of a model. Here, KNN and LR are found to be more accurate than others.

Table 5.1: SLR results

5.1.1 SLR analysis

Table 5.1 displays articles and the conclusions drawn from it. These research papers helped in selecting the supervised machine learning algorithms for this research. It can be clearly seen from SLR that SVM, KNN and LR are performing well in the mentioned articles. These algorithms tend to scale high for multi-dimensional data [8], have a reasonable training time and relatively less resource consumption to produce satisfactory results. These articles tend to answer RQ1. Although, Neural network was also a possible option but was not considered for the research because of its high computational requirements and longer training time [51]. In [2], NN and SVM were found to be almost same performance, with a huge difference in computation resources consumption. NN is slightly better, but comes with a huge cost. In [43], [9], [42], SVM performed better than NN. Compared to NN, SVM was found to be very fast and simple to use [11]. Neural networks are black box, and have limited ability to figure out casual relationship between dependent and independent variables [51]. For this study, if a NN were to be trained, it would probably take days or maybe weeks to perform decently.

Using SLR, the factors affecting the accuracy of machine learning algorithms are found to be

- The amount of training data used for an algorithm [25].
- Features extracted from the data and their relevance [12].
- Quality/cleanness of input data [20] (non-redundant) and tuning of parameters used [8].

5.2 Experimental results and analysis

The three algorithms which are SVM, k-NN and Logistic Regression were trained to classify 12 different classes, using the same data, to be able to make fair comparisons of their performances. Here, the results are divided into several sections. Firstly, the shortlisted algorithms are compared using 10-fold cross validation technique. Secondly, performances of single UE and multiple UE scenarios are shown separately.

The best performance of each algorithm is presented in the form of a confusion matrix, showing the number of classified narrow beams. X-axis in the matrix represents the labels classified by machine learning algorithms and Y-axis represents the true label (selected as per 3GPP algorithm).

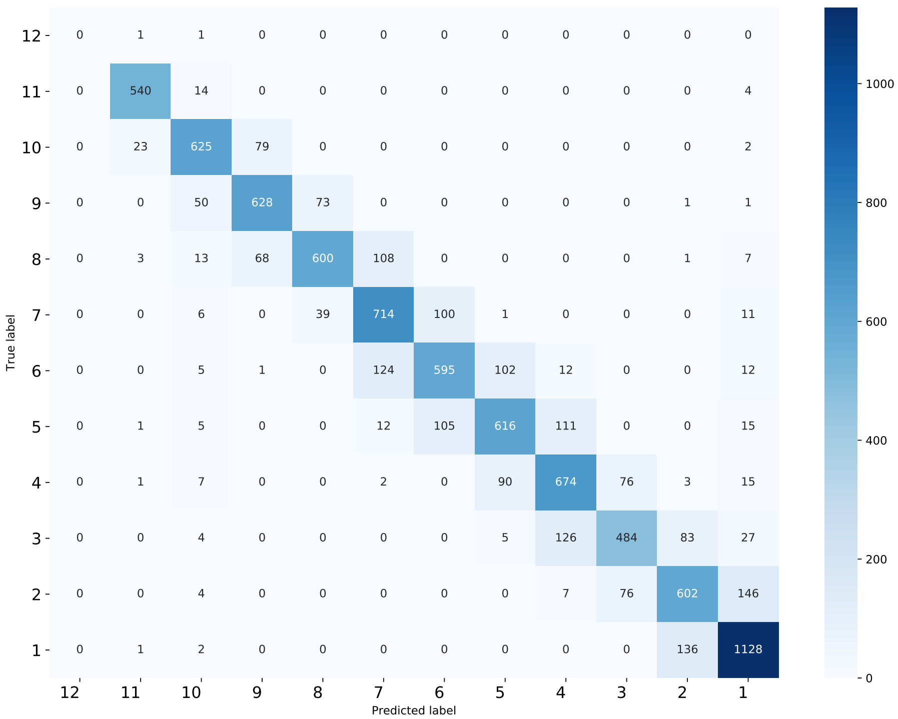

Figure 5.1: Support vector machines.

In figure 5.1, confusion matrix for SVM algorithm is shown. The matrix represents the number of instances which are correctly classified by the algorithm, for each class, as compared to the baseline algorithm. It is clear that, the most correctly classified classes are represented using dark shade and vice-versa. Class 1 has most number of correctly classified instances i.e. "1128" and class 12 has the least i.e. "0".

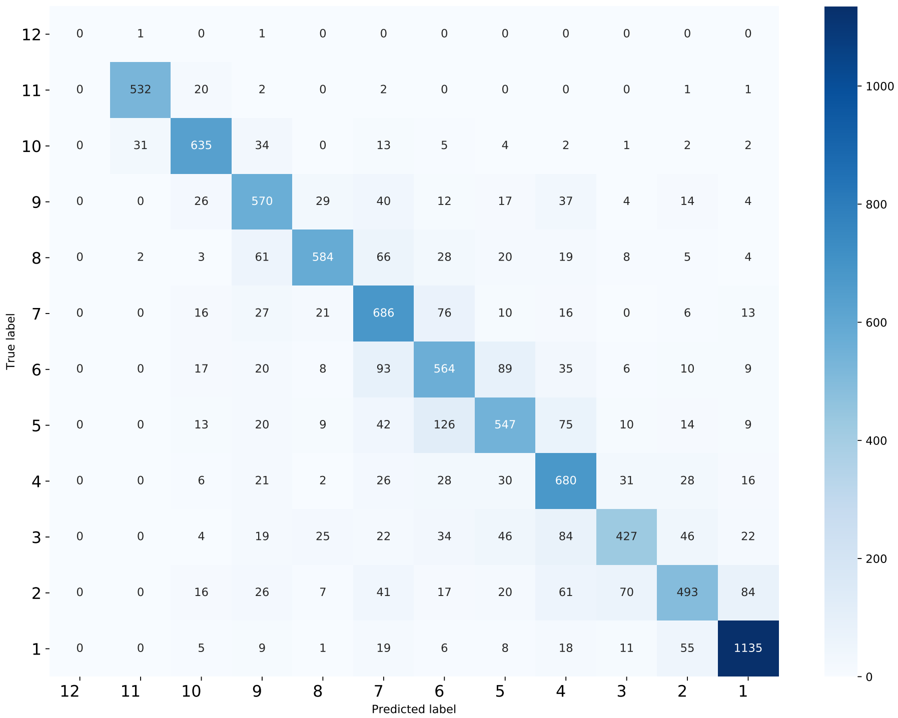

Figure 5.2: k-nearest neighbor.

Figure 5.2 represents confusion matrix for k-NN algorithm. It is visible that most number of correct instances are "1135" for class 1 and least are "0" for class 12. The classification figures for each class varies, depending on the quantity of data used in the training process.

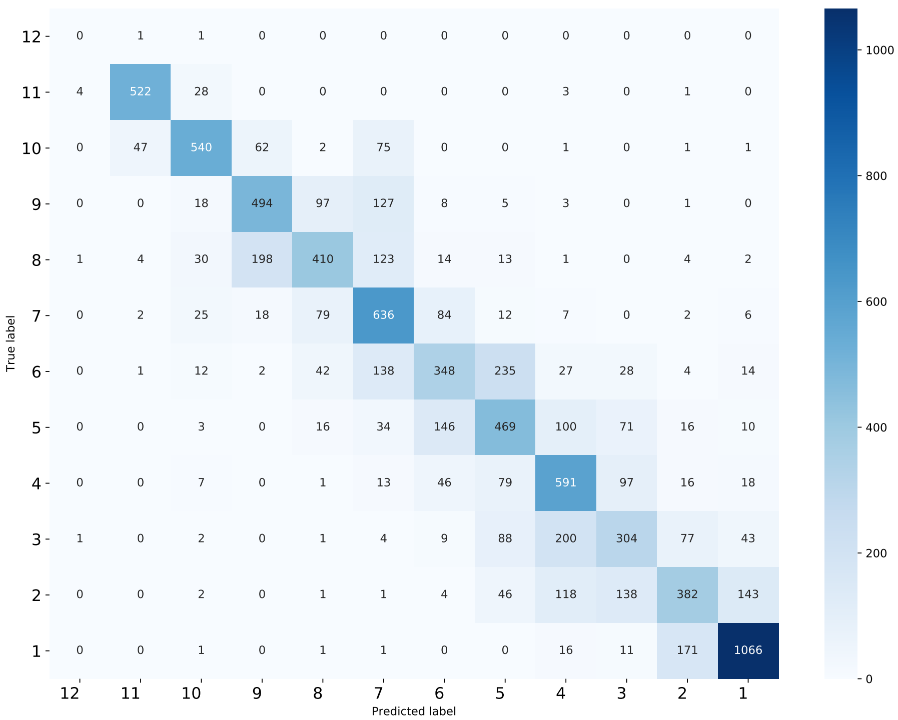

Figure 5.3: Logistic regression.

Figure 5.3 shows the confusion matrix for Logistic Regression algorithm. The maximum correctly classified instances belongs to class 1, i.e. "1066" and the least to class 12, i.e. "0". All the three algorithms behave similarly. It can also be observed that the percentage of neighbor beam selection by each algorithm is significant. This can be explained by the resemblance in RSRP values in the training data, when the narrow beams are located closer to each other.

10-fold cross validation is performed for all the three algorithms and accuracies are displayed in form of table including the deviation, which represents the percentage of neighbor beam selected by algorithms i.e. any of the beams just next to the beam selected by the baseline algorithm. Table 5.2 summarizes the performance of each algorithm.

	Accuracy after 10 fold cross validation	Neighbour beam
Support vector machines	**75.79%**	**18.95%**
K-nearest neighbor	66.62%	12.28%
Logistic regression	61.88%	24.81%

Table 5.2: Performance of machine learning algorithms in offline mode.

From the above analysis, it is clear that SVM outperforms other algorithms. Apart form the accuracy achieved, some other advantages of using SVM are; SVM always finds global maximum [8], is easy to understand and implement. We further import this trained model in Ericsson's simulator to test its performance. To do so, two scenarios are considered;

- Single user scenario.
- Multiple users scenario.

Single UE scenario

To test the accuracy of SVM in the simulator, a new random seed is selected and simulation is run for 1000 seconds using the simulation configuration mentioned in the simulation section. About 9000 samples were considered for testing the accuracy of the SVM model. The best accuracy of the SVM algorithm outside the simulator is shown in table 5.3.

Accuracy of SVM (offline)	78.5082 %
Deviation of 1 narrow beam (neighbour beam)	19.7436 %
Deviation of more than 1	1.7482 %

Table 5.3: Best performance of SVM.

Comparison between the RSRP of narrow beams selected by baseline and SVM is done, as shown in the graph 5.4. Probability distribution and cumulative distribution curves are plotted for both the algorithms to visualize the two algorithms easily.

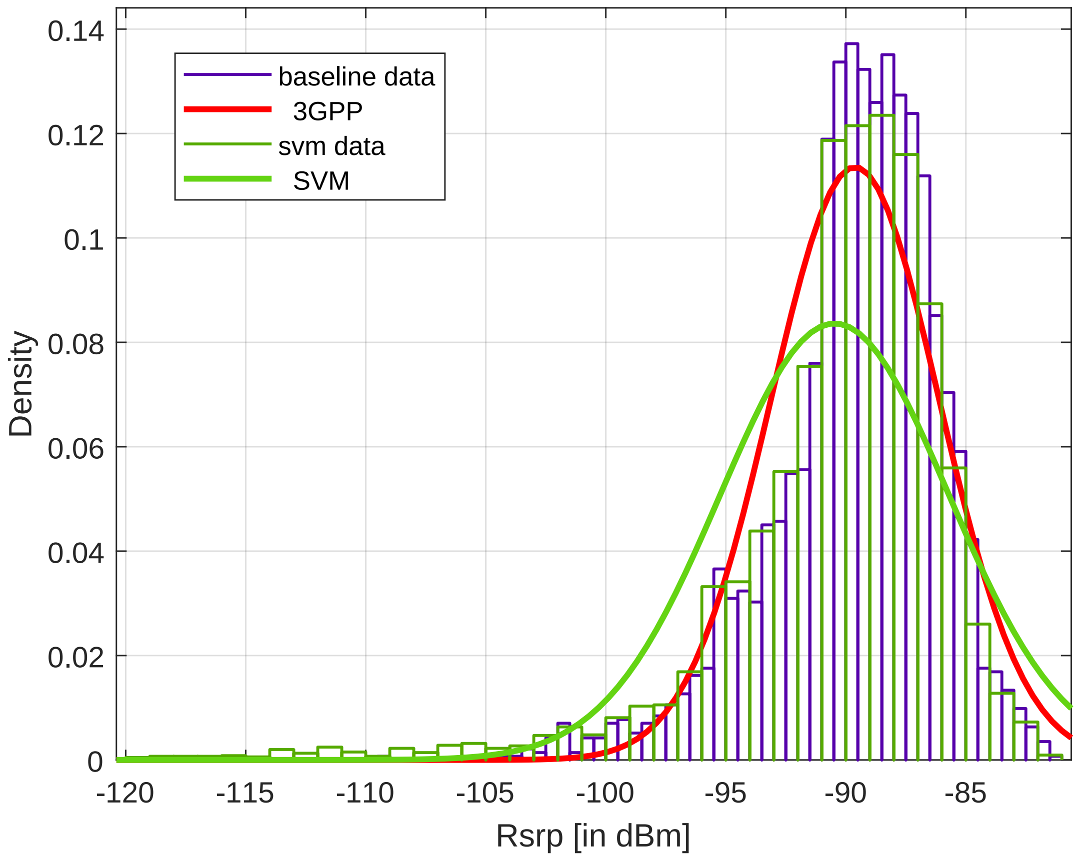

Figure 5.4: Probability distribution graph comparing Baseline (red) and SVM (green) behavior.

Figure 5.4 clearly represents the graphical comparison between SVM and Baseline algorithms and their behaviour, using the data collected from running the simulation. RSRPs between both the algorithms are plotted in normal distribution where x-axis represents the RSRP value and y-axis represents the density (number of times a particular RSRP value is selected). Since, the baseline always picks the best RSRP narrow beam, the peak of baseline is higher than SVM. SVM curve tend to be more uniform and has lower peak, because the SVM does not always selects the best narrow beam. Hence, it is reflected on the RSRP of the selected narrow beam. Plotted data is collected in a single simulation, meaning all the configuration including the speed, the mobility pattern, the seed, etc are the same for both the algorithms to be able to make fair comparison.

The SVM algorithm performs similar to the baseline algorithm. There is an average of only 2 dB difference in the magnitude of RSRPs between the baseline and the SVM algorithm. Nevertheless, this RSRP loss can be reflected at lower throughput, which can be leveraged by the gain of more downlink slots when using the SVM algorithm.

Cumulative density graph is also plotted using the same data, to analyse the behaviour more clearly. It is visible that both the algorithms have similar behaviour which satisfies the aim of the experiment for a single UE case.

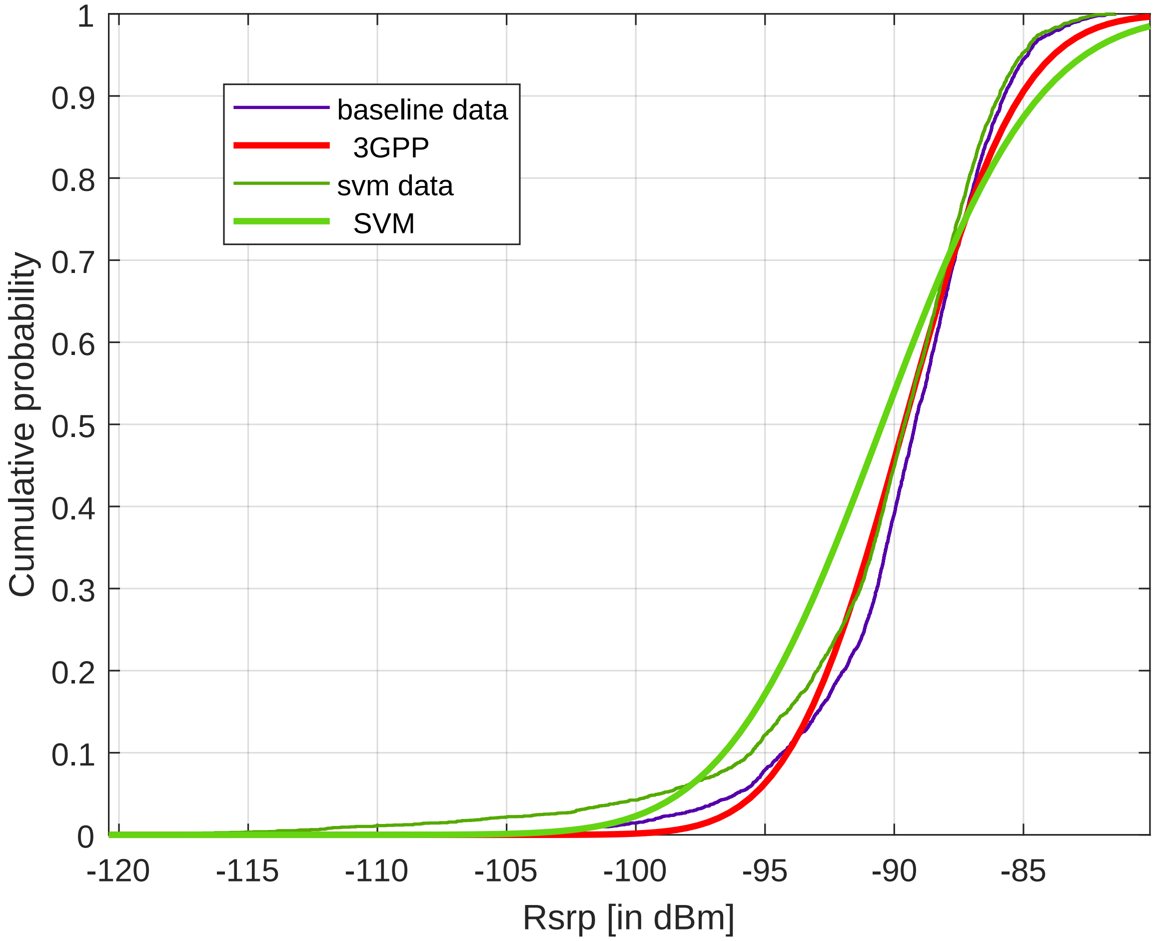

Figure 5.5: Probability distribution graph comparing Baseline (red) and SVM (green) behavior.

Cumulative curve in general shows the probability of a random observation is less than or equal to the corresponding y value. In the figure 5.5 cumulative curve for baseline algorithm (red) is shifted towards right compared to the SVM algorithm (green), meaning more narrow beams have RSRPs in range of [-95, -80] for 3GPP behaviour and [-100, -80] for SVM.

The SVM model is integrated into the simulator and its performance is tested in terms of narrow beam index selected. The SVM model is used to select the narrow beam inside wide beam 8 and is plotted by using color coding technique.

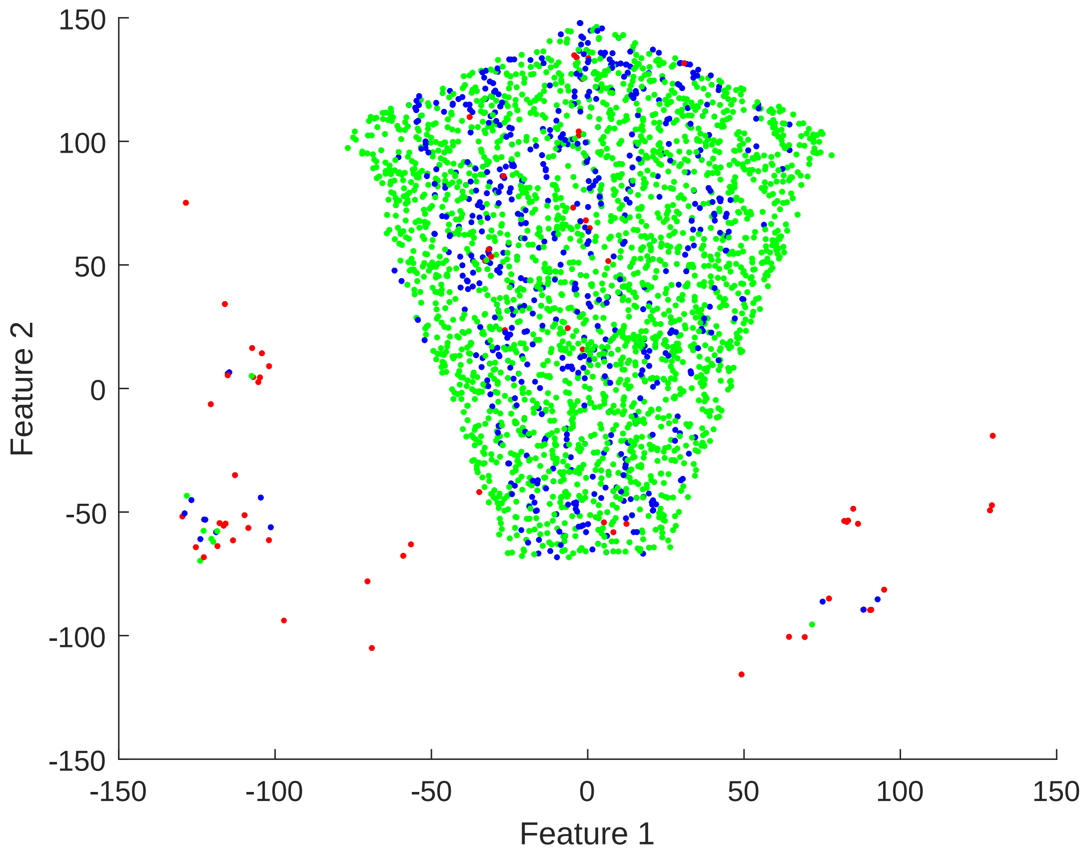

Figure 5.6: SVM performance inside wide beam 8. Green represents the UE with correctly classified narrow beam, blue means the second best beam and red means the UE with bad beam.

Figure 5.6 represents the accuracy of SVM when used in the simulator. As seen in the image, most UEs are connected to the best narrow beam (green), some to second best (blue) and bad narrow beam is seldomly selected. Most of the bad classification seems to happen in the side lobes, which had always been a problem for the machine learning algorithms. Nonetheless, SVM performance is found to be satisfactory inside the main lobe. Table 5.4 represents the accuracy of SVM in the simulator.

Correct beam prediction	78.3 %
Neighbor beam prediction	19.6 %
Bad beam prediction	2.1 %

Table 5.4: Performance of SVM in the simulator.

Narrow beams inside wide beam 8 are plotted using the SVM and the baseline algorithm and are placed side by side to be analysed and gain some insights.

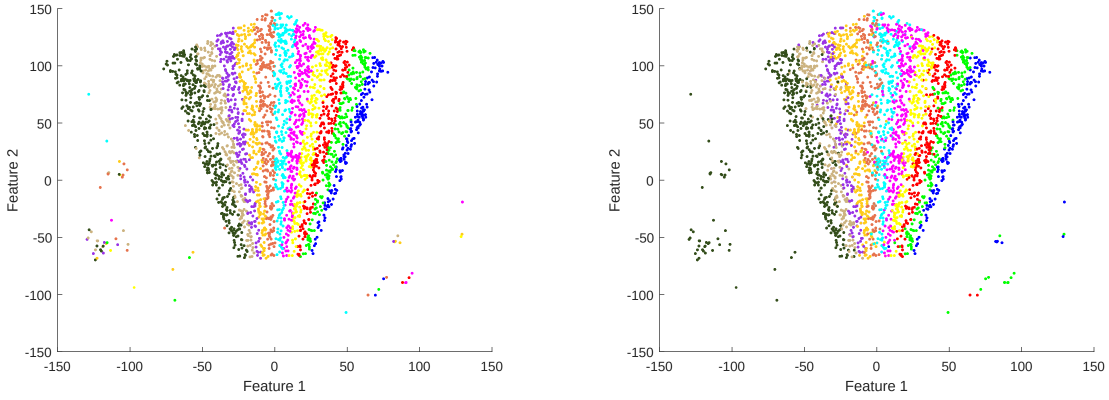

Figure 5.7: Comparison of narrow beams between (a) Baseline and (b) SVM

Some observations can be made based on the figure 5.7

- Narrow beam '1' is not being used at all by either of the algorithms i.e. only 11 narrow beams are clearly visible.
- Boundaries between the baseline algorithms are more clear compared to the SVM.
- In the SVM algorithm, UEs connected to the side lobes are assigned the nearest/second nearest narrow beam.

Multiple UE scenario

In this case several UEs are considered as mentioned in the simulation configuration section 4.4.1. Several combinations of testing the algorithms are possible but the most interesting are found to be the high speed with different SSB reporting intervals.

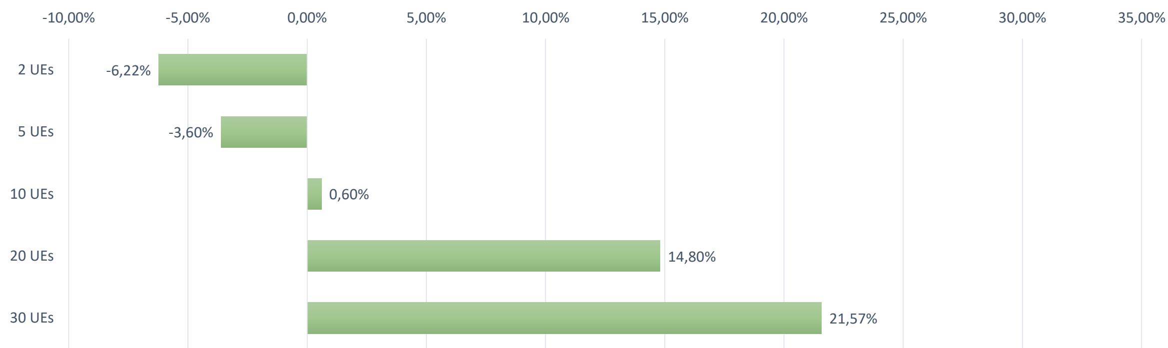

Figure 5.8: Compares the average downlink throughput of baseline to SVM algorithm with increasing number of UEs in 40ms SSB reporting interval moving at a speed of 10m/s.

Graph in 5.8 shows the performance of SVM algorithm as the number of UEs are increased in 40ms SSB interval configuration and speed of 10m/s moving in a circle inside wide beam 8. It is visible that for a number of UEs less than 10, the baseline algorithm has a better throughput. For UEs more than 10, SVM starts to outperform the baseline algorithm. This is because the SVM algorithm does not always pick the best narrow beam for data transmission, but when a greater number of UEs is considered, the average downlink throughput seems to increase, as a larger number of downlink slots are being used for data transmission. The highest throughput gain for 40 UEs is found to be 29.40%.

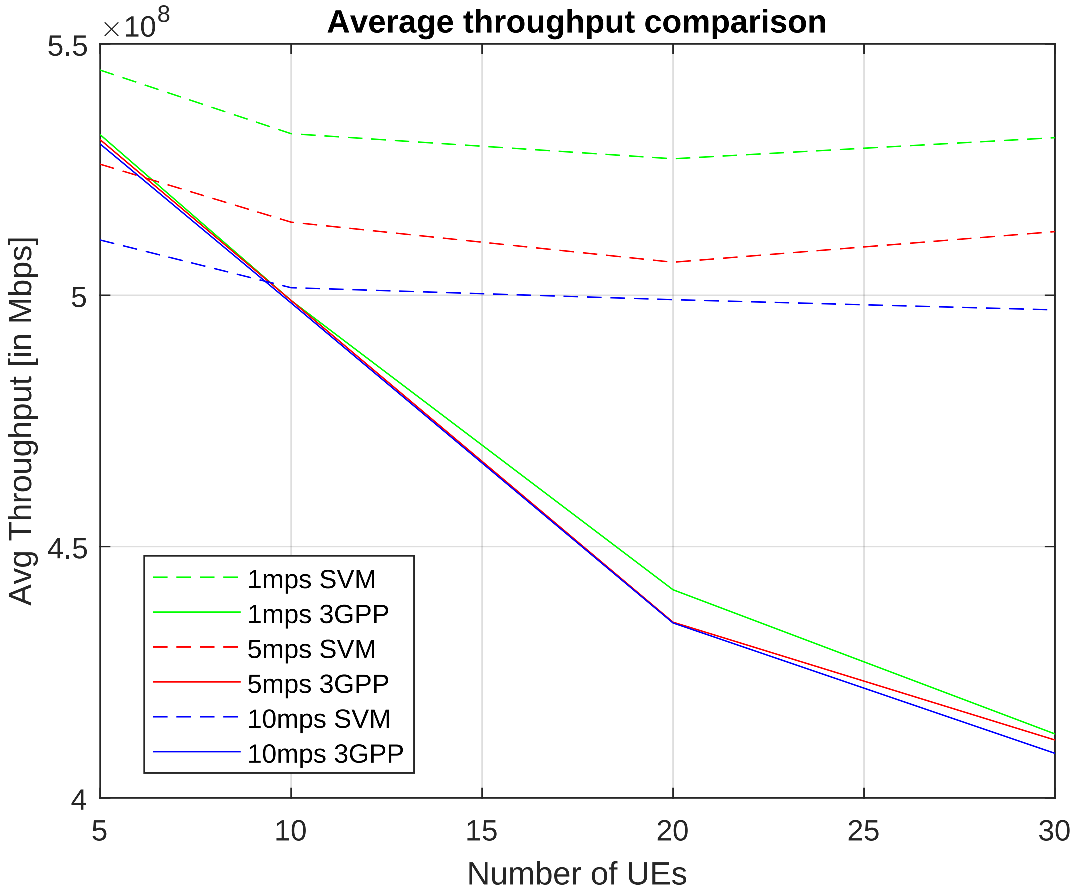

Figure 5.9: Compares the average downlink throughput (in Mbit/s) for the baseline and the SVM algorithm for 40ms SSB interval with different speeds as the number of UEs increase.

Observations from the figure 5.9

As the speed of UEs is increased, there is a decrease in average throughput. This is expected, because the narrow beam has to be updated as the UE moves. Every 40ms, the SVM selects the narrow beam based on SSB measurements, with increased speed of UEs the frequency of narrow beam switch remains the same, resulting in UEs connected to the previous beam. Hence, for slower speed the average downlink throughput is comparatively higher.

Similar comparison is made for when the CSI-RS reporting interval is 20ms.

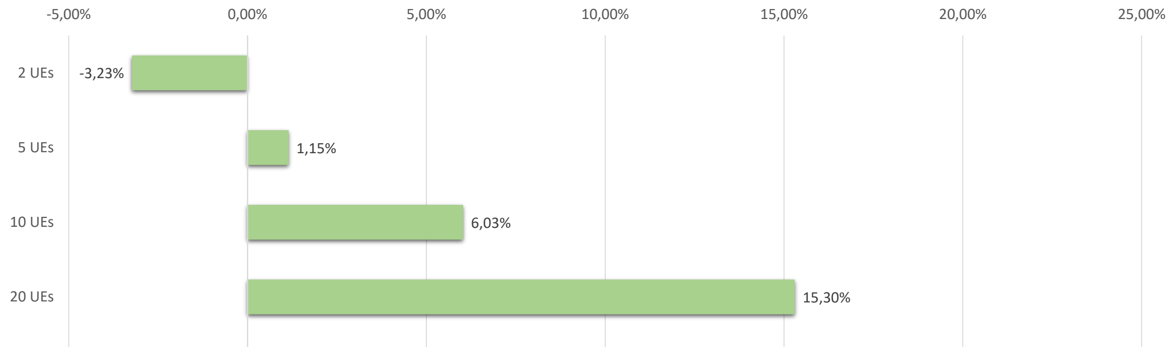

Figure 5.10: Average downlink throughput gain of SVM compared to the baseline with increasing number of UEs in 20ms SSB reporting interval moving at a speed of 10m/s.

Up to 30 UEs are considered for the 20ms scenario. When compared to the baseline algorithm, the throughput difference is shown in the figure 5.10 where, breakpoint for the SVM algorithm is observed after 5 UEs. This behaviour is justified, as the SVM model is being called more frequently when compared to the 40ms scenario. The highest throughput gain for 30 UEs is found to be 21.15%.

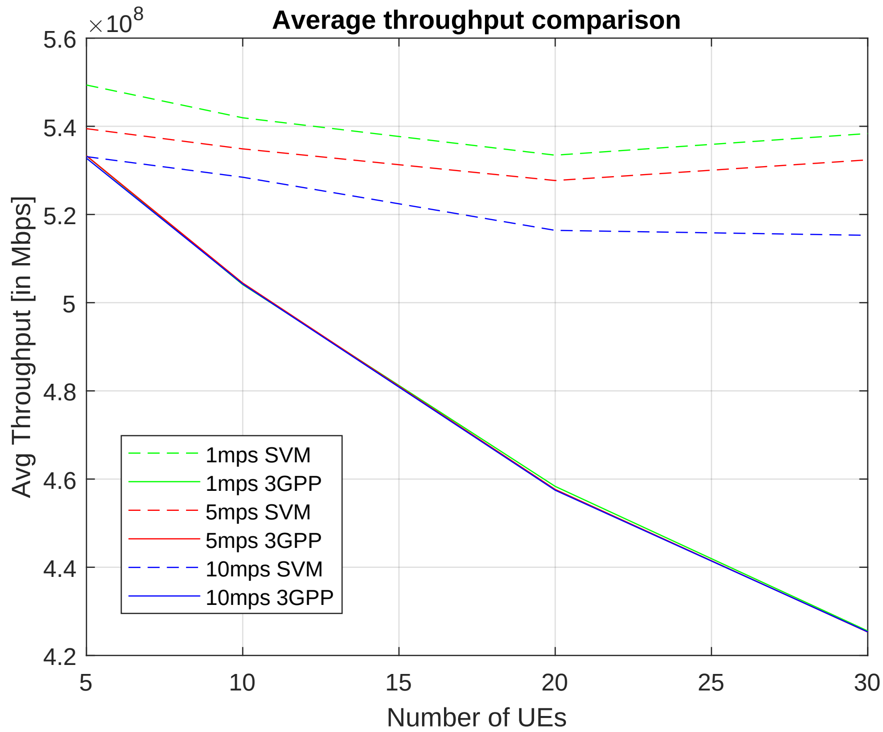

Figure 5.11: Average downlink throughput (in Mbit/s) for the baseline and the SVM algorithm for 20ms SSB interval with different speeds as the number of UEs increase.

Observing graph 5.11 there is not much variation found in behaviour of baseline algorithm. Although, changes in the average throughput of the SVM algorithm as speed and number of UEs are varied is clearly visible. For lower speed the average downlink throughput is more, as compared to higher speed. Nevertheless, the average throughput is always higher than the baseline algorithm after 5 UEs.

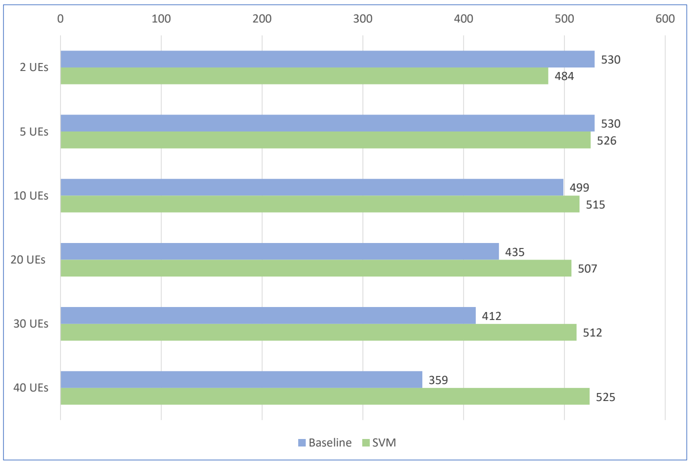

Figure 5.12: Average downlink throughput (in Mbit/s) for the baseline and the SVM algorithm for 40ms SSB interval with speed 5m/s as the number of UEs increase.

In graph 5.12 Average throughput is shown comparing the baseline with the SVM for UEs moving with speed 5m/s. Similar pattern is observed in this scenario but the magnitude of throughput is higher when compared to UEs moving with 10m/s. Break-point for the SVM algorithm in this case is found to be after 10 UEs. For 40 UEs the gain in average throughput is 46.6% when using SVM algorithm.

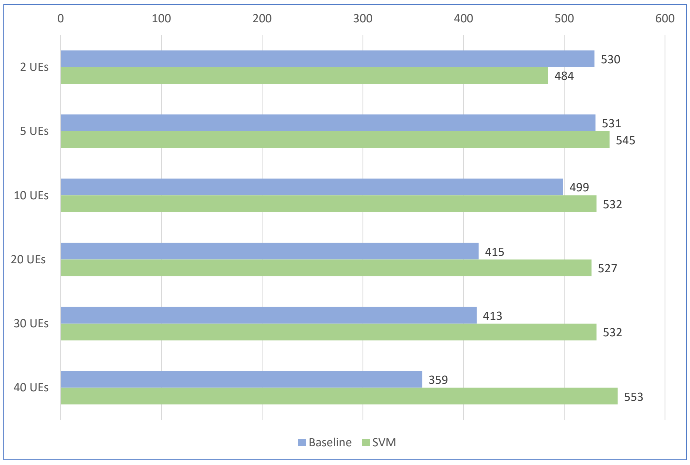

Figure 5.13: Compares the average downlink throughput (in Mbit/s) for the baseline and the SVM algorithm for 40ms SSB interval with speed 1m/s as the number of UEs increase.

In graph 5.13 comparison is made for UEs moving at the speed of 1m/s. Here, the SVM algorithm outperforms the baseline after 5 number of UEs. 54% of throughput gain is noted in this scenario.

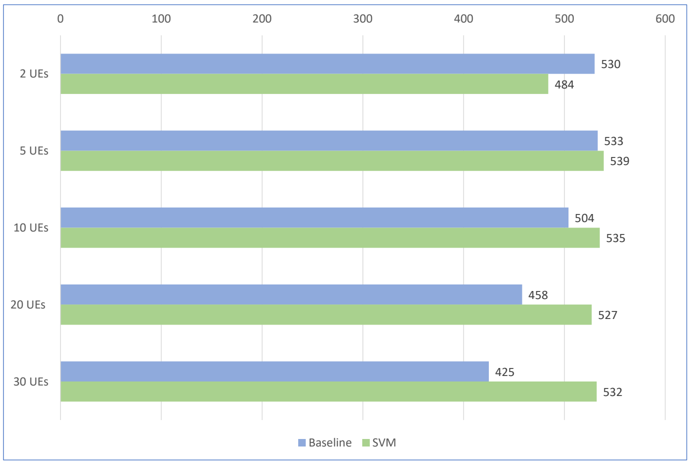

Figure 5.14: Average downlink throughput (in Mbit/s) for the baseline and the SVM algorithm for 20ms SSB interval with speed 5m/s as the number of UEs increase.

For 20ms SSB interval case, a maximum of 30 UEs are considered. In graph 5.14 the SVM algorithm starts to outperform the baseline algorithm after 5 number of UEs at 5m/s. When considering 30 UEs the average throughput gain is found to be 25.1%.

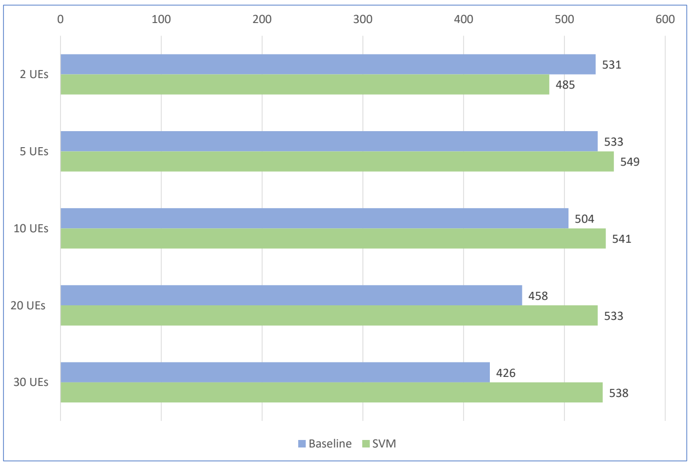

Figure 5.15: Average downlink throughput (in Mbit/s) for the baseline and the SVM algorithm for 20ms SSB interval with speed 1m/s as the number of UEs increase.

In graph 5.15 for 30 UEs the throughput gain is 26% as compared to the baseline algorithm. Hence, it can be seen that for larger number of UEs there is always some gain in total throughput, irrespective of CSI-RS reporting interval and speed of UEs when machine learning is utilized.

Chapter 6

Discussion

The results presented in section 5 indicate, that Machine learning algorithms are directly affected by the relevance of features extracted, the quality and the quantity of data used for training purpose.

Through the experiment conducted, it is observed the total cell capacity can be improved significantly when machine learning models are integrated in 5G environment. Not only the SVM algorithm was found to be most accurate for the problem defined, the usage of algorithm also shows more than 50% gain in total throughput in some scenarios and have found to match our expectations.

Maximum gain in total throughput is only found for when a large number of users are simulated simultaneously as a larger amount of scheduling slots are not being used for CSI-RS reporting. This implies, that for a large number of users moving together, a higher cell capacity can be achieved.

6.1 Threats to validity

This section covers the validation threats involved in the study and their mitigation. Methodology used in this study is according to the rules as described in [27] and [47].

6.1.1 Internal Validity

Internal validity reflects the correctness of a research. In this study, the comparison of performance of three different algorithms is shown, along with the gain in total throughput when the algorithm is applied to use. To make sure the quality of data is unaltered, the raw data has been utilized, features extracted are relevant and algorithms chosen for the experiment have proven to perform well in the past.

6.1.2 External Validity

External validity is the measure of extent to which the results found in the study can be utilized. This directly depends on the limitation of the experiment, i.e. the study is performed considering line-of-sight (LOS) between the UE and the gNodeB.

Additionally, Ericsson simulator has been used throughout the study, scope of which is limited to Ericsson itself. So, in order to replicate the study, this must be considered.

6.1.3 Conclusion Validity

Conclusion validity involves the usage of appropriate metrics for any comparison made throughout the experiment. To mitigate the same, relevant metrics were used in the entire research and suitable parameters were compared to extract the conclusion.

Chapter 7

Conclusion

In this thesis, the usage of a machine learning algorithm for selecting a narrow beam inside a wide beam is examined. Three different algorithms were considered namely, Support Vector Machines (SVM), k-Nearest Neighbor (kNN) and Logistic Regression (LR) using SLR methodology. Out of which the SVM algorithm is found to perform best, with an accuracy of 78.5% when tested offline. This algorithm is plugged into the Ericsson simulator and tested to perform acceptable with an accuracy of 78.3% and 19.6% of times the UE selects a neighbor narrow beam. Side lobes that exist in a beam tend to mislead the machine learning model, resulting in misclassification. Thus, most of the inaccurate narrow beam classification is found to be in side lobes.

Using SVM has improved the average downlink throughput significantly in multiple users scenario, by not using CSI-RS measurements in the shared channel. This leads to more availability of slots for data transmission. Therefore, an increase of 29.40% in average downlink throughput for 40ms CSI-RS reporting interval and 40 UEs is found compared to baseline algorithm also, an increase of 21.15% in average downlink throughput for 20ms CSI-RS reporting interval and 30 UEs scenario. Average downlink throughput increment was greater for 20ms interval, compared to 40ms CSI-RS reporting interval. This proves that frequent use of machine learning in updating the narrow beam leads to better throughput. Hence, increased capacity of the cell.

Finally, all the aims and objectives in the study are achieved and the research questions mentioned in the thesis are answered and justified.

7.1 Future work

Continuing the research done in this thesis, other SVM parameters configurations can be further tested inside the simulator. Similar training of algorithms/models can be done for each wide beam instead of focusing on one wide beam and trained models can be switched whenever a wide beam is changed. Training the model using the data generated in the real environment instead of using the simulated environment and analysing its performance can be compelling. Balanced dataset can be used, for improving the performance of algorithms.

Non-line-of-sight scenarios can be considered for further research. Also, analysing machine learning when beam reflections are enabled, can be interesting to explore.

Deep learning methods can be used to further improve the performance of machine learning.

References

[1] Mohammad Al Hasan, Vineet Chaoji, Saeed Salem, and Mohammed Zaki. Link prediction using supervised learning. In *SDM06: workshop on link analysis, counter-terrorism and security*, volume 30, pages 798–805, 2006.

[2] Ebrahim Edriss Ebrahim Ali and Wu Zhi Feng. Breast cancer classification using support vector machine and neural network. *International Journal of Science and Research*, 5(3):1–6, 2016.

[3] Gidudu Anthony, Hulley Gregg, and Marwala Tshilidzi. Image classification using svms: one-against-one vs one-against-all. *arXiv preprint arXiv:0711.2914*, 2007.

[4] John O Awoyemi, Adebayo O Adetunmbi, and Samuel A Oluwadare. Credit card fraud detection using machine learning techniques: A comparative analysis. In *2017 International Conference on Computing Networking and Informatics (ICCNI)*, pages 1–9. IEEE, 2017.

[5] Ahmed Badawy, Tamer Khattab, Daniele Trinchero, Tarek ElFouly, and Amr Mohamed. A simple angle of arrival estimation scheme. *arXiv preprint arXiv:1409.5744*, 2014.

[6] Joel Bill and Gustav Fahlén. Machine learning technique for beam management in 5g nr ran at mmwave frequencies. 2020.

[7] Maxime Bonneau. Reinforcement learning for 5g handover, 2017.

[8] Christopher JC Burges. A tutorial on support vector machines for pattern recognition. *Data mining and knowledge discovery*, 2(2):121–167, 1998.

[9] Evgeny Byvatov, Uli Fechner, Jens Sadowski, and Gisbert Schneider. Comparison of support vector machine and artificial neural network systems for drug/nondrug classification. *Journal of chemical information and computer sciences*, 43(6):1882–1889, 2003.

[10] Danilo Bzdok, Martin Krzywinski, and Naomi Altman. Machine learning: supervised methods, 2018.

[11] Nivedita Candade and Barnali Dixon. Multispectral classification of landsat images: a comparison of support vector machine and neural network classifiers. In *ASPRS Annual Conference Proceedings, Denver, Colorado*. Citeseer, 2004.

[12] Rhodessa J Cascaro, Bobby D Gerardo, and Ruji P Medina. Filter selection methods for multiclass classification. In *Proceedings of the 2nd International Conference on Computing and Big Data*, pages 27–31, 2019.

[13] Chih-Chung Chang and Chih-Jen Lin. Libsvm: A library for support vector machines. *ACM transactions on intelligent systems and technology (TIST)*, 2(3):1–27, 2011.

[14] Reidar Conradi and Alf Inge Wang. *Empirical methods and studies in software engineering: experiences from ESERNET*, volume 2765. Springer, 2003.

[15] Erik Dahlman, Stefan Parkvall, and Johan Skold. *5G NR: The next generation wireless access technology.* Academic Press, 2020.

[16] Elizabeth A DiGangi and Joseph T Hefner. Ancestry estimation. *Research methods in human skeletal biology*, pages 117–149, 2013.

[17] Björn Ekman. Machine learning for beam based mobility optimization in nr, 2017.

[18] Vanessa Fakhoury and Xin Zhou. User equipment characterization using machine learning. 2019.

[19] MAH Farquad and Indranil Bose. Preprocessing unbalanced data using support vector machine. *Decision Support Systems*, 53(1):226–233, 2012.

[20] Mark A Hall and Lloyd A Smith. Practical feature subset selection for machine learning. 1998.

[21] Ramkumar Harikrishnakumar, Alok Dand, Saideep Nannapaneni, and Krishna Krishnan. Supervised machine learning approach for effective supplier classification. In *2019 18th IEEE International Conference On Machine Learning And Applications (ICMLA)*, pages 240–245. IEEE, 2019.

[22] Bengt Holter. On the capacity of the mimo channel: A tutorial introduction. In *Proc. IEEE Norwegian Symposium on Signal Processing*, volume 2, pages 167–172. Citeseer, 2001.

[23] David W Hosmer Jr, Stanley Lemeshow, and Rodney X Sturdivant. *Applied logistic regression*, volume 398. John Wiley & Sons, 2013.

[24] Chih-Wei Hsu and Chih-Jen Lin. A comparison of methods for multiclass support vector machines. *IEEE transactions on Neural Networks*, 13(2):415–425, 2002.

[25] Bahareh Kalantar, Biswajeet Pradhan, Seyed Amir Naghibi, Alireza Motevalli, and Shattri Mansor. Assessment of the effects of training data selection on the landslide susceptibility mapping: a comparison between support vector machine (svm), logistic regression (lr) and artificial neural networks (ann). *Geomatics, Natural Hazards and Risk*, 9(1):49–69, 2018.

[26] Talha Ahmed Khan, Zeeshan Shahid, Muhammad Alam, MM Su'ud, and Kushsairy Kadir. Early flood risk assessment using machine learning: A comparative study of svm, q-svm, k-nn and lda. In *2019 13th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS)*, pages 1–7. IEEE, 2019.

[27] Barbara A Kitchenham, Tore Dyba, and Magne Jorgensen. Evidence-based software engineering. In *Proceedings. 26th International Conference on Software Engineering*, pages 273–281. IEEE, 2004.

[28] Sotiris B Kotsiantis, I Zaharakis, and P Pintelas. Supervised machine learning: A review of classification techniques. *Emerging artificial intelligence applications in computer engineering*, 160(1):3–24, 2007.

[29] Hyung Jun Kwon, Jung Hoon Lee, and Wan Choi. Machine learning-based beamforming in two-user miso interference channels. In *2019 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*, pages 496–499. IEEE, 2019.

[30] Congcong Li, Jie Wang, Lei Wang, Luanyun Hu, and Peng Gong. Comparison of classification algorithms and training sample sizes in urban land classification with landsat thematic mapper imagery. *Remote sensing*, 6(2):964–983, 2014.

[31] Aamir Mahmood, Muhammad Ikram Ashraf, Mikael Gidlund, Johan Torsner, and Joachim Sachs. Time synchronization in 5g wireless edge: Requirements and solutions for critical-mtc. *IEEE Communications Magazine*, 57(12):45–51, 2019.

[32] N. Maletic, V. Sark, J. Gutiérrez, and E. Grass. Device localization using mmwave ranging with sub-6-assisted angle of arrival estimation. In *2018 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB)*, pages 1–6, 2018.

[33] Nadav David Marom, Lior Rokach, and Armin Shmilovici. Using the confusion matrix for improving ensemble classifiers. In *2010 IEEE 26-th Convention of Electrical and Electronics Engineers in Israel*, pages 000555–000559. IEEE, 2010.

[34] Ajay Mathur and Giles M Foody. Multiclass and binary svm classification: Implications for training and classification users. *IEEE Geoscience and remote sensing letters*, 5(2):241–245, 2008.

[35] Melodee Montgomery, Prosenjit Chatterjee, John Jenkins, and Kaushik Roy. Touch analysis: an empirical evaluation of machine learning classification algorithms on touch data. In *International Conference on Security, Privacy and Anonymity in Computation, Communication and Storage*, pages 147–156. Springer, 2019.

[36] In Jae Myung. Tutorial on maximum likelihood estimation. *Journal of mathematical Psychology*, 47(1):90–100, 2003.

[37] R Noori, AR Karbassi, A Moghaddamnia, D Han, MH Zokaei-Ashtiani, A Farokhnia, and M Ghafari Gousheh. Assessment of input variables determination on the svm model performance using pca, gamma test, and forward selection techniques for monthly stream flow prediction. *Journal of hydrology*, 401(3-4):177–189, 2011.

[38] Aymen Omri, Mohammed Shaqfeh, Abdelmohsen Ali, and Hussein Alnuweiri. Synchronization procedure in 5g nr systems. *IEEE Access*, 7:41286–41295, 2019.

[39] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

[40] Seyedamin Pouriyeh, Sara Vahid, Giovanna Sannino, Giuseppe De Pietro, Hamid Arabnia, and Juan Gutierrez. A comprehensive investigation and comparison of machine learning techniques in the domain of heart disease. In *2017 IEEE Symposium on Computers and Communications (ISCC)*, pages 204–207. IEEE, 2017.

[41] Mahamudul Islam Sajib, Shoeib Mahmud Shargo, and Md Alomgir Hossain. Comparison of the efficiency of machine learning algorithms on twitter sentiment analysis of pathao. In *2019 22nd International Conference on Computer and Information Technology (ICCIT)*, pages 1–6. IEEE, 2019.

[42] Yang Shao and Ross S Lunetta. Comparison of support vector machine, neural network, and cart algorithms for the land-cover classification using limited training data points. *ISPRS Journal of Photogrammetry and Remote Sensing*, 70:78–87, 2012.

[43] Anju Sharma, Rajnish Kumar, Pritish Kumar Varadwaj, Ausaf Ahmad, and Ghulam Md Ashraf. A comparative study of support vector machine, artificial neural network and bayesian classifier for mutagenicity prediction. *Interdisciplinary Sciences: Computational Life Sciences*, 3(3):232–239, 2011.

[44] Muhammad Usman Sheikh, Fayezeh Ghavimi, Kalle Ruttik, and Riku Jantti. Drone detection and classification using cellular network: A machine learning approach. In *2019 IEEE 90th Vehicular Technology Conference (VTC2019-Fall)*, pages 1–6. IEEE, 2019.

[45] Archana Singh, Avantika Yadav, and Ajay Rana. K-means with three different distance metrics. *International Journal of Computer Applications*, 67(10), 2013.

[46] Marina Sokolova and Guy Lapalme. A systematic analysis of performance measures for classification tasks. *Information processing & management*, 45(4):427–437, 2009.

[47] Stanley Sue. Science, ethnicity, and bias: Where have we gone wrong? *American psychologist*, 54(12):1070, 1999.

[48] Phan Thanh Noi and Martin Kappas. Comparison of random forest, k-nearest neighbor, and support vector machine classifiers for land cover classification using sentinel-2 imagery. *Sensors*, 18(1):18, 2018.

[49] Ikram Sumaiya Thaseen and Cherukuri Aswani Kumar. Intrusion detection model using fusion of chi-square feature selection and multi class svm. *Journal of King Saud University-Computer and Information Sciences*, 29(4):462–472, 2017.

[50] Simon Tong and Daphne Koller. Support vector machine active learning with applications to text classification. *Journal of machine learning research*, 2(Nov):45–66, 2001.

[51] Jack V Tu. Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes. *Journal of clinical epidemiology*, 49(11):1225–1231, 1996.

[52] Xueli Wang, Yufeng Zhang, Hongxin Zhang, Xiaofeng Wei, and Guangyuan Wang. Identification and authentication for wireless transmission security based on rf-dna fingerprint. *EURASIP Journal on Wireless Communications and Networking*, 2019(1):230, 2019.

[53] Wikipedia contributors. Angle of arrival — Wikipedia, the free encyclopedia, 2020. [Online; accessed 25-November-2020].

[54] Min-Ling Zhang and Zhi-Hua Zhou. Ml-knn: A lazy learning approach to multi-label learning. *Pattern recognition*, 40(7):2038–2048, 2007.

[55] XIN ZHOU and VANESSA FAKHOURY. User equipment characterization using machine learning. 2019.

[56] Ji Zhu and Trevor Hastie. Classification of gene microarrays by penalized logistic regression. *Biostatistics*, 5(3):427–443, 2004.