Context Aware Initial Search in 5G mmWave Systems

By

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Approval

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Abstract

The wide bandwidth available at the millimeter wave (mmWave) frequencies is expected to offer high data rates in the fifth generation (5G) of cellular networks. The technology implements directional transmission to overcome increased path loss at high frequencies. The dependence on directionality urges to establish new control layer protocols because the algorithms implemented in omnidirectional long term evolution (LTE) systems are not suitable for these networks. The mmWave base station (BS) and user equipment (UE) need to be properly aligned for directional communication constituting long-lasting *initial access* (IA) phase. Recently, several research works have been done to devise smart IA procedures for mmWave systems. Some of these schemes periodically sweep across the cell area while others make use of the contextual information regarding BS and UE profiles and propagation environment to establish the link. This paper proposes a smart machine learning-based context-aware sequential algorithm for IA in 5G mmWave systems and analyzes its performance in comparison to the conventional exhaustive and iterative search algorithms. The algorithm is shown to provide a comparatively lower misdetection probability and a smaller discovery delay.

Dedication

To Amma who had left her precious and sincere bundle of guidance and prayers for my success and protection.

To Abbu, my ideal, who always believed in the vision of empowering education and wholeheartedly dedicated himself to this noble cause.

To Ammi who selflessly sacrificed every grain of her being to make her children worthwhile.

To Sadia Baa, the beacon of the family, to whom I always look forward for guidance and aspiration.

To Sobia Baa who always unconditionally loved and supported me in every phase of my life.

To Ruhi Baa who has always been by my side in order to fulfill my dreams.

To my pride, Bhayya, Major Ammar Zia, who always protected and cared for me.

To (Dr.) Ammara Baa who always treated me with care and affection, both literally and figuratively.

Last but not the least, to Muhammad Abdullah, Umm-e-Hani and Maiza for being my source of relief during these stressed studies.

Certificate of Originality

I hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any degree or diploma at NUST SEECS or at any other educational institute, except where due acknowledgement has been made in the thesis. Any contribution made to the research by others, with whom I have worked at NUST SEECS or elsewhere, is explicitly acknowledged in the thesis.

I also declare that the intellectual content of this thesis is the product of my own work, except for the assistance from others in the project's design and conception or in style, presentation and linguistics which has been acknowledged.

Author Name: **Rida Zia-ul-Mustafa**

Signature: ____________________

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Table of Contents

1 Introduction **1**

1.1 Motivation 1

1.2 Contribution 6

2 Groundwork on IA in mmWave Systems **8**

2.1 Sequential Cell Search 9

2.1.1 Exhaustive Search 10

2.1.2 Iterative Search 10

2.1.3 Hybrid Search 12

2.2 CA Cell Search 13

3 ML-based CA Sequential Initial Access **15**

3.1 System Model 15

3.2 IA Phase-1 17

3.3 IA Phase-2 19

4 Performance Evaluation **24**

4.1 Simulation Playground 24

4.2 Impact of Variance 25

4.2.1 Discovery Delay 25

4.2.2 Probability of Misdetection 26

4.3 Impact of PNN Training Set 27

4.4 Cell Search Sectors 28

4.5 Signal-to-Noise Ratio Threshold 30

4.6 Cell Radius 31

5 Conclusion and Future Work 33

List of Figures

1.1 FCC Spectrum Chart [1] 2

1.2 Frequency vs. Sea Level Attenuation [2] 3

1.3 HetNet and SDN-supported Architecture for mmWave Communications [3] 4

1.4 Range Mismatch Problem [4] 5

2.1 Exhaustive Search 9

2.2 Iterative Search 11

2.3 Hybrid Search 12

3.1 Fetching UE Coordinates 16

3.2 Probabilstic Neural Network 17

3.3 Cell Search 19

3.4 Proposed Algorithm Flow 22

4.1 Impact of Variance on Discovery Delay 26

4.2 Impact of Variance on Probability of Misdetection 26

4.3 Training set vs. DD PMD ($\delta^2 = 40ms^{-1}$, initial # of input nodes = 50) 27

4.4 Stages vs. Discovery Delay 29

4.5 SNR Threshold (α_{th}) vs. Misdetection Probability 30

4.6 Cell Radius vs. Misdetection Probability 31

List of Tables

4.1 Simulation Parameters 25

List of Acronyms

ML	Machine Learning
CA	Context Aware
IA	Initial Access
5G	Fifth Generation
mmWave	Millimeter Wave
LTE	Long Term Evolution
BS	Base Station
UE	User Equipment
IoT	Internet of Things
μWave	Micro Wave
HetNet	Heterogeneous Networks
SDN	Software Defined Networking
C-plane	Control Plane
U-plane	User Plane

PNN	Probabilistic Neural Network
PMD	Probability of Misdetection
DD	Discovery Delay
SNR	Signal-to-Noise Ratio
GPS	Global Positioning System

Chapter 1

Introduction

1.1 Motivation

The advent of the Internet has uplifted the standard of living, reforming this world as a Global Village. With the passage of time, a soaring increase in the Internet population has been seen due to the emergence of smart devices and the fact that the basic routine and work tasks are, now, strongly dependent and associated with the Internet [5–7]. The Telecommunications community is positively looking forward towards the coming era of the Internet of Things (IoT) where everyday devices will communicate and operate via the Internet [8]. The ongoing subscribers growth also imposes crucial limitations on the performance of traditional microwave (μWave) systems in terms of providing low latency for real-time communications as well as to support high throughput for applications including ultra-high definition video streaming or virtual reality. Fig. 1.1 depicts the two slices of United States Federal Communications Commission (FCC) spectrum chart where the upper slice

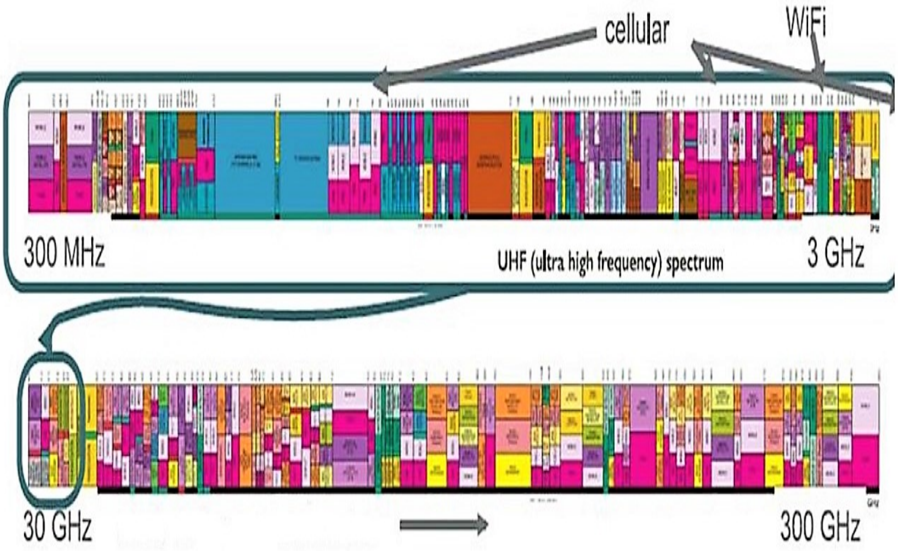

Figure 1.1: FCC Spectrum Chart [1]

is comprised of low carrier frequencies and lower slice belongs to the high frequency spectrum. The current sub-6 GHz band for conventional mobile cellular networks utilize the upper frequency slice that is heavily crunched and has also nearly approached the Shannon limit thus, inducing the interest of researchers to push the radio spectrum up to the 30-300 GHz mmWave frequency band for 5G communication systems [9–26].

The widely available and unutilized bandwidth in the mmWave spectrum is potentially expected to cater for the high data rate requirements of 5G access networks. Additionally, small wavelengths at mmWave frequencies enable to build miniaturized antenna arrays with abundant antenna elements, thereby, offering extra gains through spatial multiplexing and isolation. Moreover, mmWaves provide narrow beamwidths to allow antenna configurations that reduce the co-channel interference to provide spatial ef-

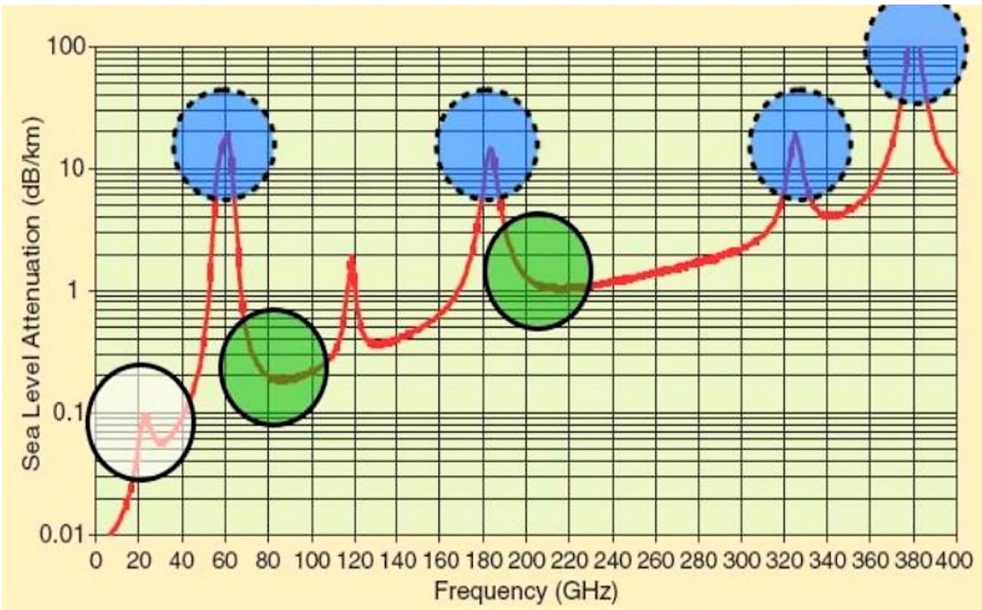

Figure 1.2: Frequency vs. Sea Level Attenuation [2]

ficiency. Alongside several benefits, the mmWave frequency band imposes significant challenges in the way to exploit its potential features. High carrier frequencies experience extreme molecular and atmospheric absorption losses alongside serious rain attenuation [27–29]. Fig. 1.2 illustrates the attenuation experienced at various operating frequencies. The blue circles mark the frequency bands having high attenuation, i.e., 60 GHz spctrum, and thus are suitable for short range indoor communications while green circles depict the frequency bands whose free space isotropic propagation loss is comparable to that of the legacy mobile communication systems, i.e., 70 GHz spectrum, and white circles correspond to the frequency bands exhibiting low attenuation, i.e, 28 GHz and 38 GHz spectrum. Studies show that a careful and appropriate link design can compensate for these losses [29].

Additionally, high carrier frequencies resulting in short wavelengths make

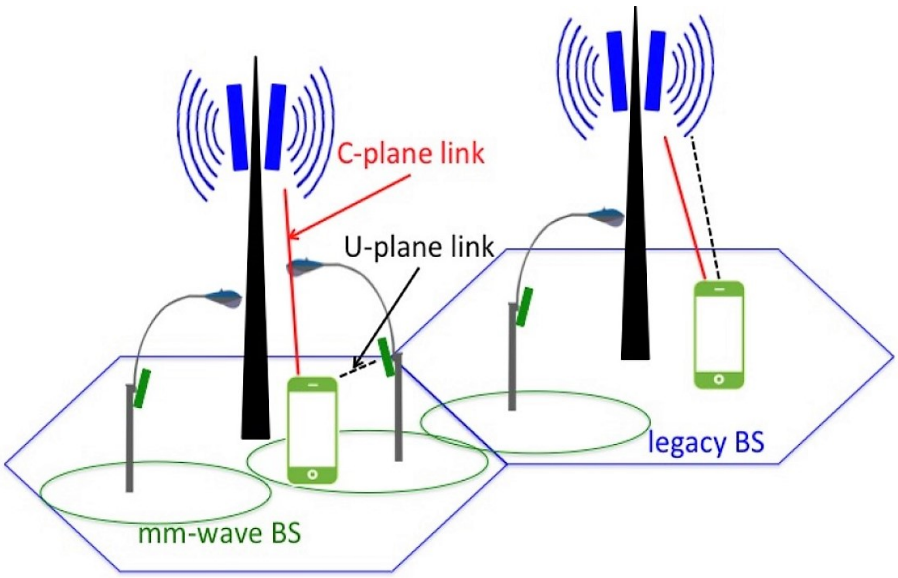

Figure 1.3: HetNet and SDN-supported Architecture for mmWave Communications [3]

mmWave signal susceptible to get around and penetrate through the blockage of solid obstacles causing severe signal attenuation [30]. Higher mmWave carrier frequencies also offer higher path loss as compared to that of traditional lower frequency communication systems thus compelling to deploy dense spatial layouts of mmWave systems with small cell radius and high gain directional transmissions for compensation [2, 31–39].

The demanding propagation impairments in mmWave channel suggest to uphold the existing μWave communication network in order to ensure persistent service and coverage [40], thus paving the way for the heterogeneous network (HetNet) model in which wide connectivity will be provided by the conventional μWave BS and mmWave BS will offer the on-demand service to the UE [41]. Also, the diverse HetNet devices propose a functional split between the control (C-) plane and user (U-) plane to deal with the signaling

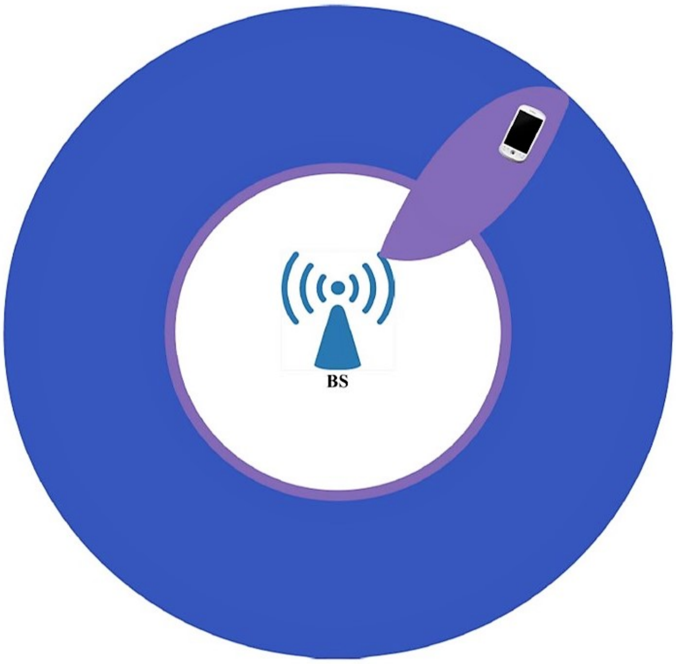

Figure 1.4: Range Mismatch Problem [4]

information and data transmission, respectively. Fig. 1.3 shows the basic HetNet and SDN supported architecture for mmWave 5G communication systems.

Furthermore, the mmWave BS and UE must be spatially aligned in order to carry out the directional transmission of signals even during the preliminary task of Initial Access (IA), the process of establishing a physical link between the BS and UE to transfer the data. Thus, the IA process of conventional LTE networks is not suitable for the mmWave systems because in LTE, initially the pilot signal is broadcasted on the omnidirectional channel. Implementing the IA process of LTE in mmWave systems will cause the range mismatch problem, i.e., difference between the range covered by directional data transfer and omnidirectional cell search [42–44]. Fig. 1.4

represents the range mismatch problem where white circle denotes the range covered by omnidirectional cell search while blue circle marks the range that is covered by using directional beam steering. The mentioned perspective urges to discover new cell search schemes for IA in mmWave communication systems.

1.2 Contribution

A tremendous amount of work is being carried out to develop efficient mmWave IA strategies, focused on improving the probability of misdetection (PMD) caused due to blockage and deafness, i.e., the beams of UE and the mmWave BS do not direct towards each other in the IA phase [45, 46], and discovery delay (DD) due to long-lasting directional sweep across the cell area to detect the UE. This work is also dedicated to designing a smart IA algorithm for 5G mmWave communication systems and analyzes its performance in comparison to the conventional algorithms. The eminent research contribution is organized in this dissertation as follows:

1. We provide a shallow insight into the various 5G mmWave IA schemes by categorizing them in two major divisions of sequential cell search and context aware cell search strategies (Chap. 2).

2. Stepping forward, we develop the conceptual and mathematical foundations to our proposed machine learning-based context aware sequential algorithm, which smartly utilizes the strengths of machine learning and context awareness alongside sequential cell search to successfully estab-

lish a connection between the mmWave base station and user equipment (Chap. 3).

3. We evaluate the performance of our devised initial access algorithm for mmWave communications via conducting comparative analysis, through numerical simulations, with the well-reputed exhaustive and iterative search algorithms. The index performance metrics are discovery delay and probability of misdetection where the prior is estimated on the number of cell sectors being searched while later is analyzed on the basis of signal-to-noise ratio threshold and the cell radius (Chap. 4).

4. Finally, we briefly elaborate the findings of our research work and identify the future open research problems related to the proposed algorithm (Chap. 5).

Chapter 2

Groundwork on IA in mmWave Systems

Communications community is diligently working on various standardization technologies for mmWave wireless local area networks (WLAN) and wireless personal area networks (WPAN), given as IEEE 802.11ad [47], IEEE 802.15.3c [48] and ECMA-387 [49, 50], to name a few.

Researchers are particularly working on devising suitable strategies for the initial access phase in 5G mmWave systems. The main focus of research studies is on reducing the discovery delay, imposed due to the long duration of directional cell search, alongside providing the minimum probability of misdetection. In this scenario, the work done so far can be categorized into two major groups, i.e., sequential cell search and context-aware (CA) cell search schemes. The key works related to these categories are detailed in the subsequent sections. Moreover, this research work is focused on analyzing IA procedure for downlink transmission thus the related work cited is also in

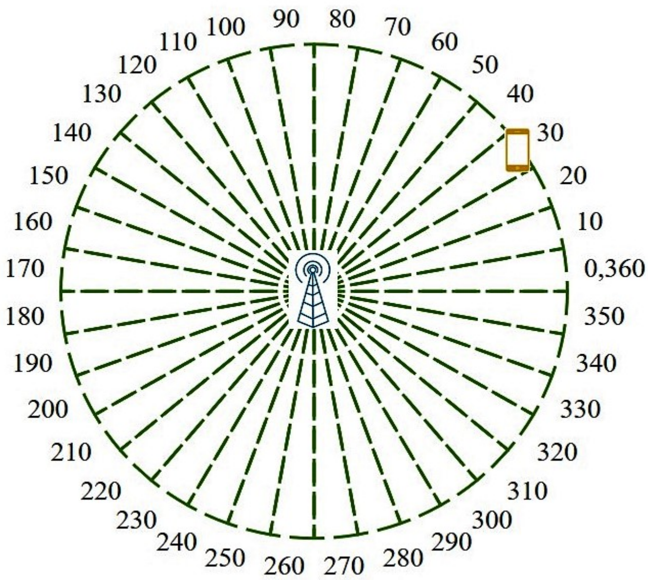

Figure 2.1: Exhaustive Search

accordance with the scope of the dissertation.

2.1 Sequential Cell Search

Sequential cell search schemes, as the name suggests, refer to the strategies that sequentially span the 360^o cell area, following a predefined codebook based directional beamforming. Codebook is a matrix such that each column defines the weight vector of antennas associated to a particular beam pattern. The prominent algorithms under this category are summarized in the adjacent subsections.

2.1.1 Exhaustive Search

One of the preliminary sequential cell search procedures is the exhaustive search in which the mmWave BS has predefined beam directions to periodically scan across the cell area [51]. Exhaustive search starts scanning the 360° cell area from 0° with a narrow beamwidth, commonly 10°. It points the beam in a particular sector for a certain time duration and if UE is not detected, algorithm will wait a while and then steer the beam towards the adjacent sector in anticlockwise direction. The process repeats until UE is connected or BS has searched the entire cell area till 360°. As, exhaustive search spans the cell area with a narrow beamwidth providing larger gain and range to establish the link hence causing a lower probability of misdetection. Meanwhile, algorithm needs to span across 36 cell sectors with a beamwidth of 10° in 360° cell area thus causing a larger discovery delay. Fig. 2.1 illustrates the sector sweep in exhaustive search.

2.1.2 Iterative Search

In [52], iterative cell search scheme is analyzed in which mmWave BS firstly spans the cell area in two sectors with a wide beamwidth of 180° where first sector corresponds to 0° to 180° and second sector is associated with 180° to 360°. If UE is connected in a sector, the process eventually terminates otherwise algorithm further divides the particular search region and beamwidth based on a loose signal-to-noise ratio (SNR) threshold that specifies the probability of a UE to be present within that sector, i.e., if loose SNR threshold suggests that UE could potentially be located in search region of 0° to 180°,

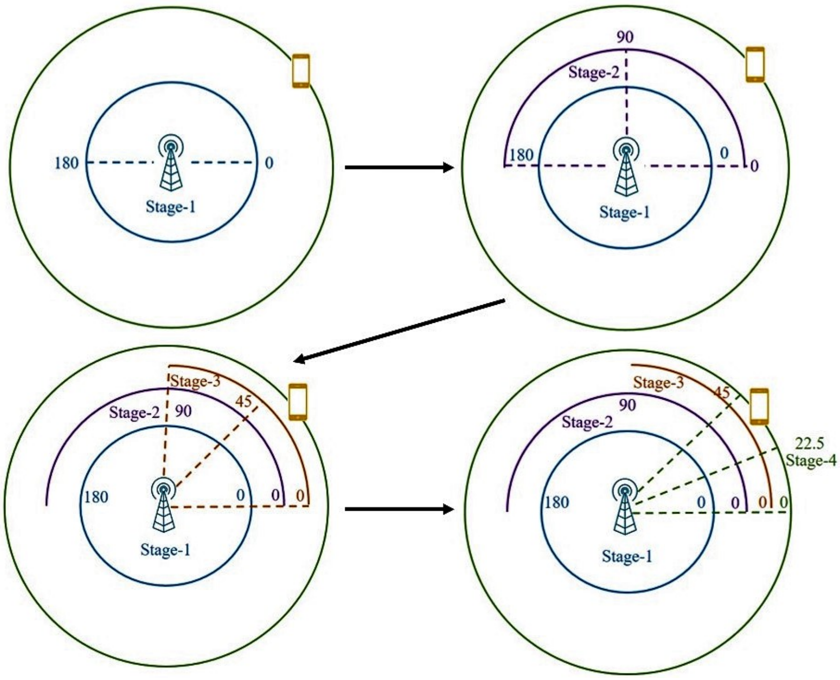

Figure 2.2: Iterative Search

iterative search splits and searches the given area in further two sectors of 0° to 90° and 90° to 180° respectively with a beamwidth of 90°. The process continues until UE establishes a link with BS or beamwidth approaches to its minimum predefined limit. Iterative search systematically spans the cell area and offers lower discovery delay on the expense of higher probability of misdetection. Initially the wider beamwidth spans across the large cell area providing lower gain and range to detect the UE while on later stages beamwidth is narrower but the cell sectors being searched are smaller in area. Fig. 2.2 depicts the sector level search in iterative algorithm.

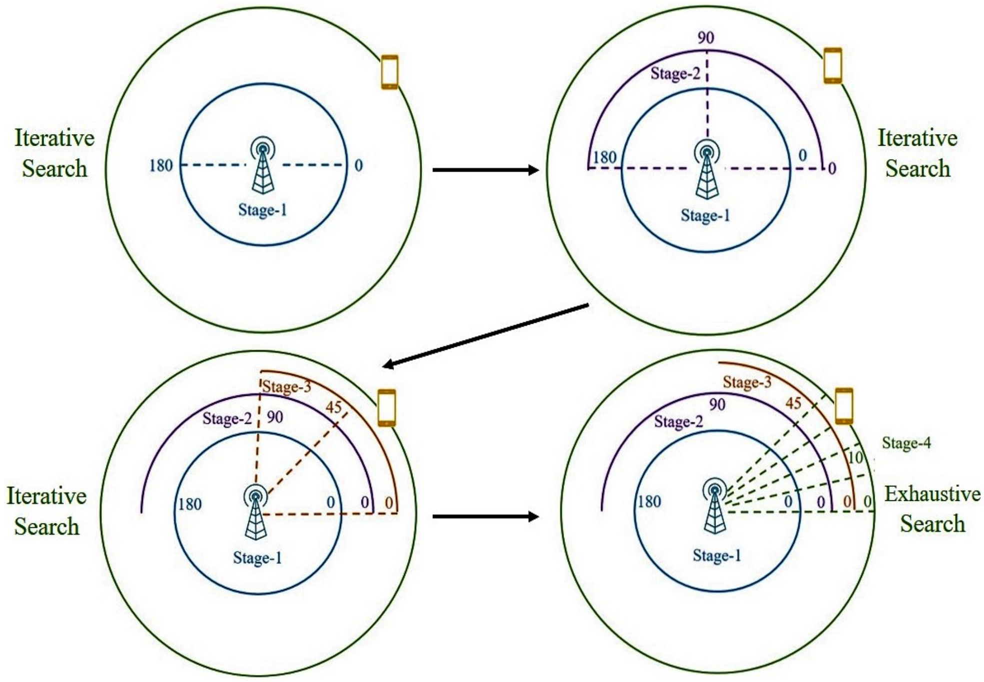

Figure 2.3: Hybrid Search

2.1.3 Hybrid Search

Comparative analysis of exhaustive and iterative search schemes reveals that the prior offers the lower probability of misdetection with narrow beamwidth and high gain to provide connectivity to a larger range of cell area with longer search duration whereas the later is capable of providing much lower discovery delay on the expense of high probability of misdetection [53].

Hence, a hybrid algorithm is proposed in [20] that merges the strengths of exhaustive and iterative algorithms to provide a balanced tradeoff between discovery delay and probability of misdetection. Hybrid search firstly performs iterative search on broad cell sectors with wide beamwidths to reduce discovery delay as compared to that of exhaustive search, and if the UE is not connected until the last pair of sectors is reached then the algorithm implements the exhaustive search within these sectors to provide a lower probability of misdetection than that of iterative search. Fig. 2.3 shows the search sequence of hybrid algorithm.

2.2 CA Cell Search

CA cell search schemes are expected to exploit the available contextual information regarding the BS and UE location profiles, network quality requirements and the propagation environment, to establish the connection. As mmWave systems exploit higher range of frequencies as compared to the existing conventional networks, it is comparatively more prone to high isotropic path loss as suggested by the Friis free space path loss equation (FSPL) [54], i.e., isotropic propagation loss is proportional to the square of the frequency (f)

$$FSPL = (4 \times \pi \times R \times f)^2 \tag{2.1}$$

where R is the distance between transmitting and receiving antennas. High path loss causes coverage issues in mmWave systems thus emphasizing on retaining the available μWave communication systems in order to provide better UE connectivity, which is termed as the HetNet scenario. The diverse nature of communication devices operating and interacting at different frequencies paves the way to deploy SDN architecture that enables a functional split between signalling information and data transmission and permits to assign bulk of signalling tasks to the legacy base stations, which resultantly assists to gather the UE contextual information and opens the doors to a new dimension of mmWave cell search schemes [55].

The concept of designing mmWave IA algorithms utilizing contextual information is comparatively new in literature but various related studies have been conducted in recent years that suggest to implement the algorithms that make use of BS and UE position information [56], environmental characteristics [57], past access attempts [58], power levels received after initial scan [59] and time of arrival (ToA)/angle of arrival (AoA) information to propose a pair of best possible beamwidth and search direction to form the connection [59].

Incorporation of artificial intelligence in contemporary systems is gaining momentum these days [60]. Recently, the trending domain of ML is also being deployed alongside CA algorithms to impose significant performance improvements as compared to that of conventional algorithms. Machine learning is implemented in [3] that utilizes the context information regarding UE's past access attempts, in a HetNet and SDN supported scenario, to learn the best possible pair of beam candidates to establish the link.

Chapter 3

ML-based CA Sequential Initial Access

3.1 System Model

The ML-based CA sequential algorithm for IA in 5G mmWave systems aims to incorporate the strengths of artificial intelligence with the availability of contextual information, which, in our case, is the location information of BS and UE, in devising a suitable beamwidth to establish the connection.

Consider an environment with the presence of both stationary and mobile UEs, making requests for connection with the mmWave BS. Also, the system is GPS coordinated in order to extract the respective locations of UE and BSs. The global positioning system (GPS) coordinates initially gathered are referred as the estimated coordinates because UE could potentially has deviated from its original position. Conventional algorithms, i.e., exhaustive and iterative searches, do not concern for the scenarios of mobile UE whereas

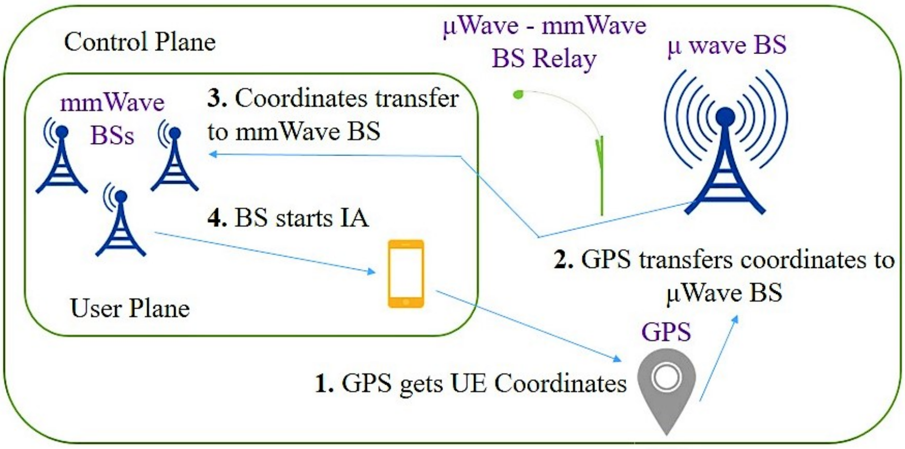

Figure 3.1: Fetching UE Coordinates

the proposed algorithm has the ability to deal with such cases by utilizing the ML model. Moreover, we are assuming a software defined networking scenario, i.e., a centralized C-plane is responsible for transferring signaling information and a U-plane is designated to handle the data transmission. Additionally, a HetNet environment is considered such that we have a μWave BS and several associated mmWave BSs.

Holistically the suggested process of IA works as follows. Firstly, the UE initiates a connection request via C-plane and network determines an appropriate mmWave BS for that particular UE keeping minimum distance as a parameter. Afterward, the μWave BS transfers the GPS coordinates of linked mmWave BS to the associated UE and the UE directs its beam towards the linked mmWave BS. Meanwhile, as the linked mmWave BS is aware of the UE coordinates, it determines the optimal beamwidth according to the proposed scheme, described in the sequel, to establish a successful connection. The setup pocess is shown in Fig. 3.1. For ease of analysis, we are examining the process of IA only on the BS side.

3.2 IA Phase-1

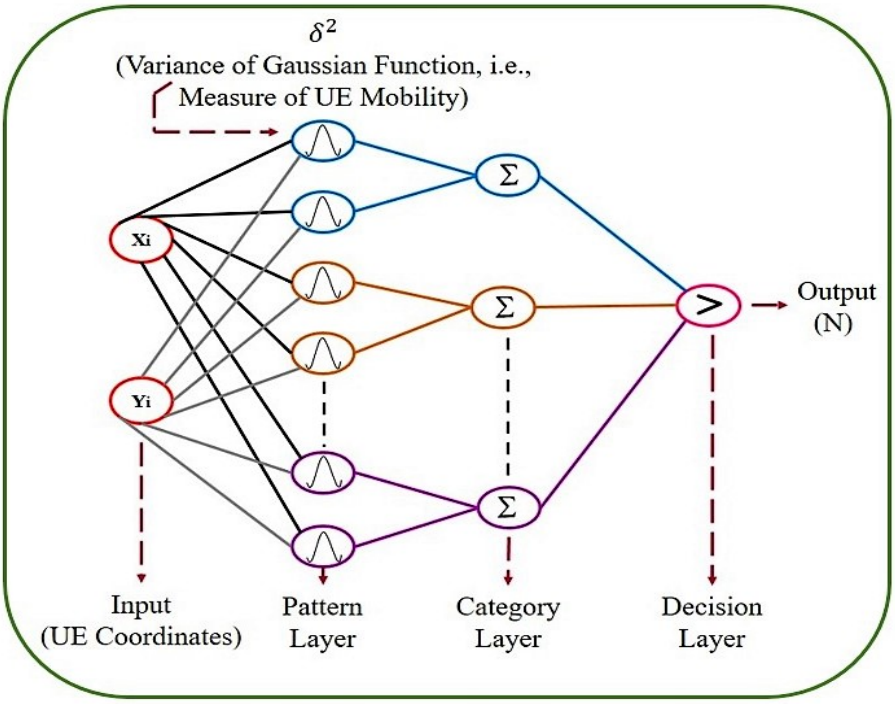

Figure 3.2: Probabilstic Neural Network

mmWave BS obtains and feeds the estimated GPS coordinates of UE to the input layer of the ML model, which is a probabilistic neural network (PNN), as shown in Fig. 3.2. PNN is a feed-forward neural network, generally utilized in classification and pattern recognition scenarios. PNN architecture is comprised of four layers. The first layer, which is stated as the input layer, holds the training set of already classified data points, i.e., x-coordinates and y-coordinates of UEs that established a successful connection with the mmWave BS, in the past. When the input layer gets the estimated x and y coordinates of the new UE, it will form a data point corresponding to a pattern unit in the second layer, just like other trained data points. Pattern unit is basically a Gaussian function with a peak centered on the estimated UE location. For example, if the UE's estimated coordinates are represented as x_o and y_o, then the value associated to each pattern unit can be computed by considering the distance between the UE 's coordinates (x_o, y_o) and the center of pattern unit, associated to trained data points (x, y). Thus, the corresponding Gaussian function is given as

$$f(x,y) = exp - \left\{ \frac{(x - x_o)^2 + (y - y_o)^2}{2\delta^2} \right\}, \tag{3.1}$$

where δ is the constant that controls the width of the function. Conceptually, δ accounts for the variance of UE's mobility, i.e., if δ has large value, algorithm is suitable to perform for highly mobile UE, else if δ is small, the Gaussian function is narrower in width around its center that is appropriate for stationary or slightly mobile UE. δ can be predefined by keeping in view the environment in which BS is deployed and the precision of the estimated GPS location.

Moving forward, the pattern units for each category are summed to create a category unit in the third layer of the neural network. In our case, a category unit corresponds to the cardinality (N) of I, where I is a set of natural numbers whose elements, $i \in I$, represent the number of cell search sectors. Training the network is automatic, i.e., adding new data points to the appropriate category set.

After obtaining the suggested number of cell sectors for search (N), the optimal beamwidth (BW_{opt}^{o}) for the process of IA in a 360^o cell area is given as

$$BW_{opt}^{o} = \frac{360^o}{N}. \tag{3.2}$$

3.3 IA Phase-2

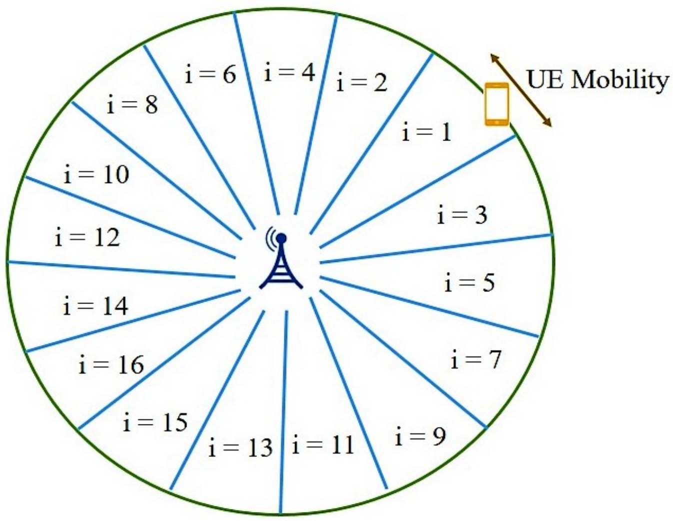

Figure 3.3: Cell Search

Once the algorithm acquires the BW_{opt}^{o}, it starts performing the cell search as depicted in Fig. 3.3. Firstly, it points the beam towards the sector, n, having estimated UE location at θ_n degrees, for T_{sig} seconds to establish the connection. If UE is not discovered at sector n for $i = 1$ (first step), then after a period of T_{per} seconds, the algorithm will steer the beam by increasing a sector in positive direction, i.e., $n+1$ for $i = 2$ followed by $n-1$ for $i = 3$, $n+2$ for $i = 4$, $n-2$ for $i = 5$, and so on. The search region for even values of i is given as

$$\theta_S^o = (i+1) \times BW_{opt}^{o} + \theta_n, \tag{3.3}$$

$$\theta_E^o = i \times BW_{opt}^o + \theta_n, \tag{3.4}$$

whereas the search region corresponding to odd values of i is determined as

$$\theta_S^o = (i-1) \times BW_{opt}^o + \theta_n, \tag{3.5}$$

$$\theta_E^o = i \times BW_{opt}^o + \theta_n, \tag{3.6}$$

where θ_S^o identifies the start of the beam and θ_E^o indicates the end of the beam. The algorithm terminates the IA if UE is not found until i reaches N.

Moving forward towards the other parameters for establishing the connection. Consider $G(\theta)$ be the total antenna gain, given as

$$G(\theta) = G_{tx} \times G_{rx} \times BFGain_{tx} \times BFGain_{rx}, \tag{3.7}$$

where G_{tx} and G_{rx} are the gains at transmitter and receiver antennas, respectively. It should be noted that we are considering sectored approximation, i.e., the search beam provides a constant gain in a sector while ignoring the influence of side lobes. Also, $BFGain_{tx}$ and $BFGain_{rx}$ are transmitter and receiver analog beamforming gains, respectively. BFGain is given as

$$BFGain = E \times D, \tag{3.8}$$

where E stands for antenna efficiency and D corresponds to antenna directivity, which is defined as

$$D = \frac{4\pi}{BW_{opt}^o}. \tag{3.9}$$

The beam will encounter either a line-of-sight (LoS) or non-line-of-sight (NLoS) channel while searching a sector. In reality, the gain provided by the mmWave link is affected by channel inaccuracies caused by diffraction, fading, scattering, etc., but these factors are ignored for the simplicity of our analysis. Thus, consider the channel path loss to be

$$L(r) = \begin{cases} \rho + 10\alpha_L log(r) + \chi_L & \text{if the link is LoS,} \\ \rho + 10\alpha_N log(r) + \chi_N & \text{otherwise,} \end{cases} \tag{3.10}$$

where ρ is the fixed path loss factor, α_L and α_N are LoS and NLoS path loss exponents, respectively, r is the mmWave link distance, while χ_L and χ_N correspond to LoS and NLoS zero mean lognormal random variable, respectively that accounts for shadowing.

In our analysis, we have considered the same blockage model as utilized by Bai and Heath [61], given by

$$\Xi = e^{-\beta r}, \tag{3.11}$$

where β parameter is evaluated by considering the statistics of buildings and r corresponds to the mmWave link distance. Utilizing the analysis for real world environment conducted in [14], we have concluded that if $1 > \Xi(r) \geqslant 0.5$, the link is LoS and if $\Xi(r) < 0.5$, the link will be NLoS. The LoS and NLoS scenarios define whether the envelope follows a Rician or Rayleigh distribution, respectively.

Moving forward, if UE gets a signal from the mmWave BS, then the received power, P_r is calculated as

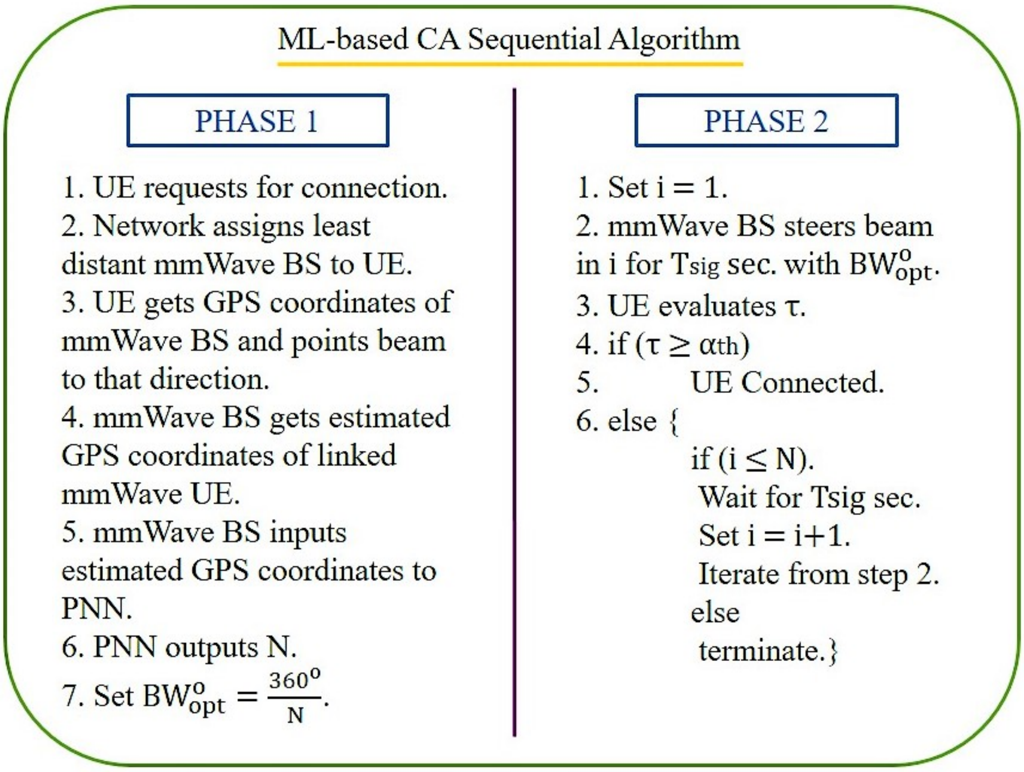

Figure 3.4: Proposed Algorithm Flow

$$P_r = \frac{P_t G(\theta)\mu}{L(r)}, \tag{3.12}$$

where P_t denotes the transmit power of the BS and μ is the squared envelope of multipath fading. Interference due to other UEs will be ignored as we are analyzing one mmWave BS and one UE scenario. Hence, the received signal-to-noise ratio (SNR), τ, is defined as

$$\tau = \frac{P_r}{\sigma^2}, \tag{3.13}$$

where σ^2 accounts for the noise power. The UE is connected with the associated mmWave BS if

$$\tau \geqslant \alpha_{th}, \tag{3.14}$$

otherwise, the link will not be established where α_{th} represents the SNR threshold. The proposed algorithm flow is illustrated in Fig. 3.4.

Considering that the UE has been successfully detected, we calculate the discovery delay, DD, i.e., the time spent for discovering the UE. DD for a particular sector $i \epsilon I$ is given as

$$DD(i) = i \times T_{sig} + (i - 1) \times T_{per}. \tag{3.15}$$

The total discovery delay for a given UE is the sum of discovery delay for each sector searched until the UE is connected.

Chapter 4

Performance Evaluation

4.1 Simulation Playground

The efficiency of the proposed IA search scheme is analyzed by taking into consideration the number of input nodes used to train the PNN and the variance factor (δ^2). Moreover, the performance of exhaustive, iterative and proposed ML-based CA sequential algorithm is evaluated by means of comparative analysis executed by numerical simulations. For simplicity, it is considered that the mmWave BS performs analog beamforming where the effect of atmospheric losses, rain attenuation, and molecular absorption losses is ignored in a cell radius of 100 meters. The simulation parameters are listed in Table 4.1.

The algorithms are assessed in terms of two key performance indicators, i.e., discovery delay and the probability of misdetection. Once a UE is connected to the mmWave BS, the discovery delay is measured over the sectors being searched until UE detection. Probability of misdetection depends on

Parameter	**Value**	**Parameter**	**Value**
f_c	73 GHz	Average UE Requets	20000
P_t	30 dBm	Bandwidth	2 GHz
α_L	2	T_{sig}	10µsec.
α_N	2.45	T_{per}	200 µsec.
Std(χ_L)	5.2 dB	Std(χ_L)	7.2 dB
α_s	20 dB	α_{th}	40 dB
G_{tx}	24.5 dBi	G_{rx}	24.5 dBi
Noise Figure	10 dB	$BFGain_{rx}$	4 dBi

Table 4.1: Simulation Parameters

several factors but most importantly on cell radius, i.e., UE-BS distance, and received SNR, thus PMD is analyzed with respect to these parameters. Moreover, simulations are approximated over 10^5 Monte Carlo iterations.

4.2 Impact of Variance

4.2.1 Discovery Delay

Conceptually, variance (δ^2) of Gaussian function in the pattern layer of PNN accounts for the sensitivity of the network towards the UE mobility. We are working within a cell radius of 100 meters and UE follows a uniform distribution, $U[1, 100]$ ms^{-1} in case of mobility. We can approximately categorize the UE mobility as slow mobile ($1-40$ ms^{-1}), medium mobile ($40-80$ ms^{-1}) and high mobile ($80-100$ ms^{-1}). It is evident from the graphs in Fig. 4.1 that discovery delay is the highest for the value of δ^2 corresponding to the set of slow mobile UE. Whereas, when the network is trained for medium to high mobile UE scenarios, the discovery delay is significantly reduced.

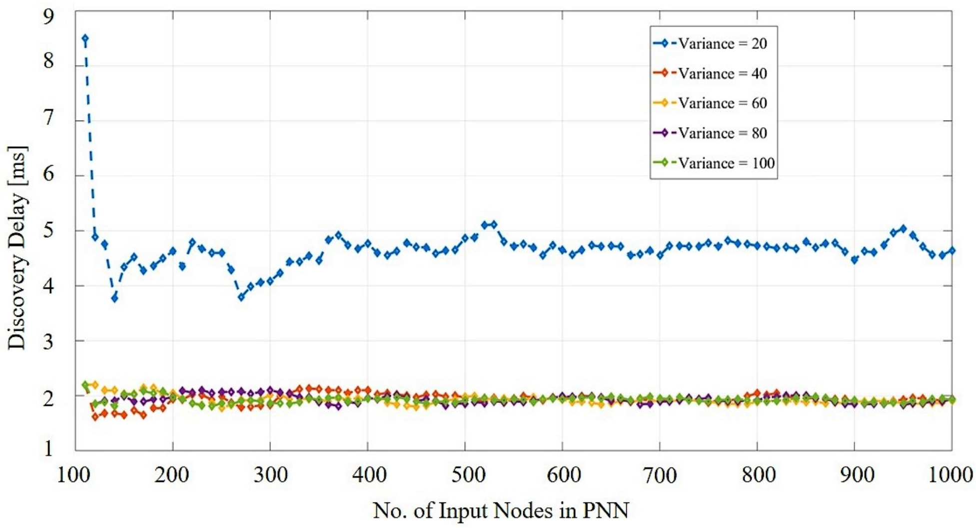

Figure 4.1: Impact of Variance on Discovery Delay

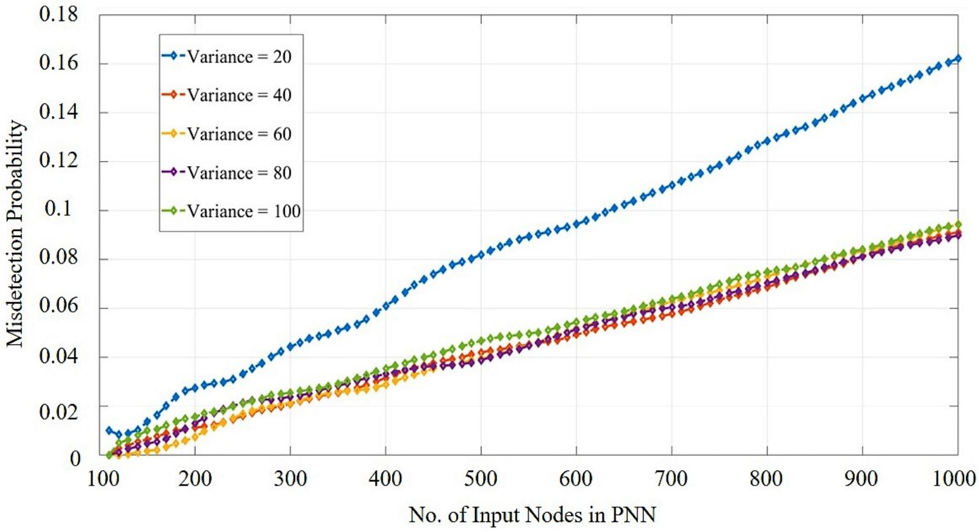

Figure 4.2: Impact of Variance on Probability of Misdetection

4.2.2 Probability of Misdetection

Analyzing the probability of misdetection on various values of variance in Fig. 4.2 reveals that the PMD is highest if we choose δ^2 corresponding to the set of slow mobile UE, i.e. $20ms^{-1}$. The second high curve is obtained on considering the δ^2 for the scenario of highly mobile UE, i.e., $100ms^{-1}$.

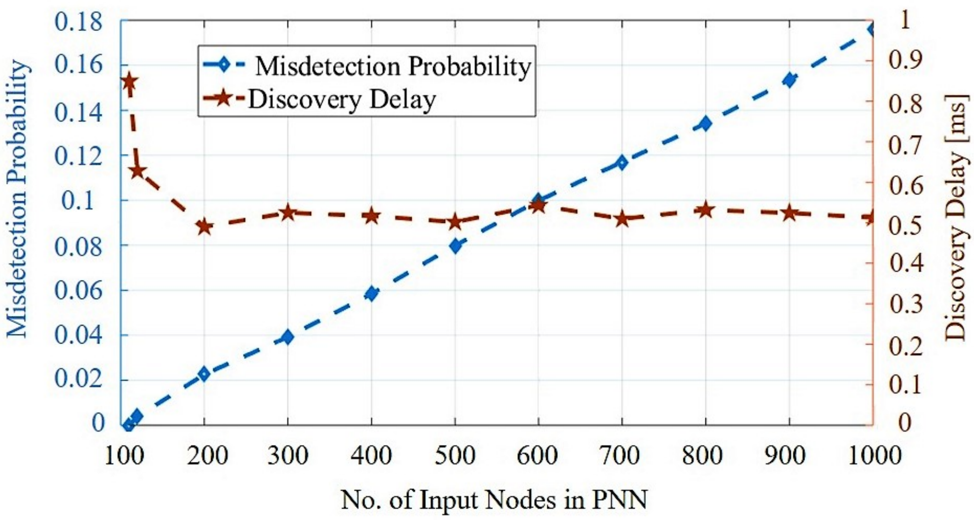

Figure 4.3: Training set vs. DD PMD ($\delta^2 = 40ms^{-1}$, initial # of input nodes = 50)

The overall analysis suggests to take the value of variance from the set of medium mobile UE ($40 - 80\ ms^{-1}$) so, in our analysis, we are considering $\delta^2 = 40ms^{-1}$.

4.3 Impact of PNN Training Set

Fig. 2.3 shows that as the training set increases from 100 (50 new data points) to 1000 (950 new data points), the discovery delay decreases from 0.9 ms to 0.5 ms. The significant decrease happens when training set is comprised of 200 input nodes, the discovery delay is approximately sustained for further increase in data points. Basically, increase in number of training nodes will result in more accurate classification of the UE location in associated category, i.e., the optimum number of search sectors that will eventually cause an improvement in the time taken to sweep across the cell area thus decreasing discovery delay. On the contrary, the probability of misdetection is continuously increasing with an increase in the number of training nodes. It goes from 0.01 to 0.18 for an increase of 100 to 1000 in the number of training data points. This might be due to the fact that as the number of input nodes representing estimated UE coordinates is increased the network becomes more trained for devising a beamwidth in accordance to the particular UE location whereas there are several other factors, i.e., path loss exponent, LOS and NLOS fading, blockage environment etc. that also have significant impact towards the UE detection but PNN being unaware of these features results in an increase in the PMD. Nevertheless, this limitation serves as a motivation for conducting future work that could incorporate the information of these factors in the PNN for improved performance.

4.4 Cell Search Sectors

The only system parameter directly related to DD is the number of cell sectors being searched during the IA phase. More the sectors, longer is the time taken by an algorithm to span the area, thus increasing the DD. Bar graphs in Fig. 4.4 analyze the performance of the algorithms in terms of DD. It is evident that the exhaustive search scheme provides the highest DD, because it searches the 360^o cell area with fixed beamwidth of 10^o in counterclockwise direction starting from 0^o until I reaches its cardinality. On the contrary, iterative search, in the first stage, spans the 360^o region with 180^o beamwidth, if the UE is connected, the process of searching stops automatically, otherwise based on a loose SNR threshold, which suggests that

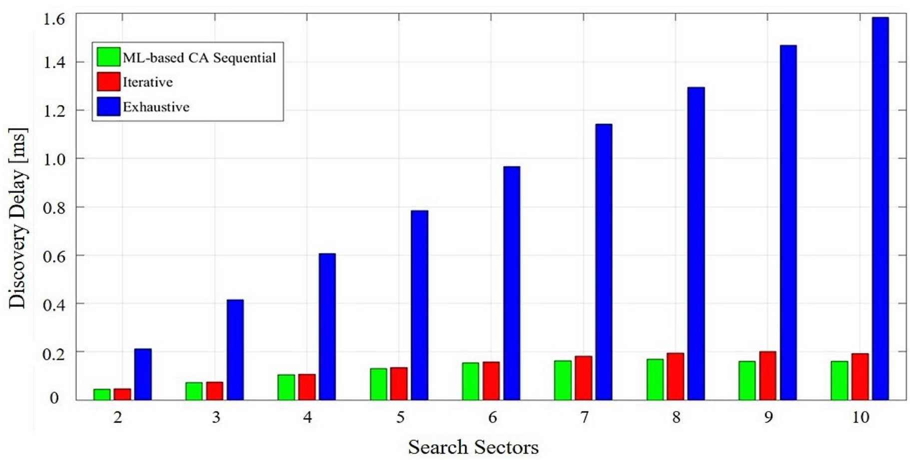

Figure 4.4: Stages vs. Discovery Delay

UE could potentially be located in the particular sector, algorithm further divides the sector and the beamwidth into half and search till maximum of five stages (2 sectors in each stage) stopping at a beamwidth of 11.25^o. As iterative search spans the 360^o area by smartly reducing the number of sectors as compared to the consecutive sector sweeps of exhaustive search, the DD of iterative search in contrast to that of exhaustive search is significantly lower.

Lastly, the ML-based CA sequential search utilizes the availability of UE's location information to predict the most appropriate beamwidth, responsible for connection, and then directly points the beam towards that location. If the connection does not establish, the algorithm searches the area nearby to UE's given location in a way that if the UE is supposed to be at sector n, and does not connect, it searches the sector $n-1$, then $n+1, n-2, n+2$ and so on till N. As, context aware algorithm, based on UE's location smartly designs the beamwidth and also the sequence of sectors to be searched as opposed to the arbitrary search of exhaustive and iterative methods, the DD of context aware search is lowest of them all.

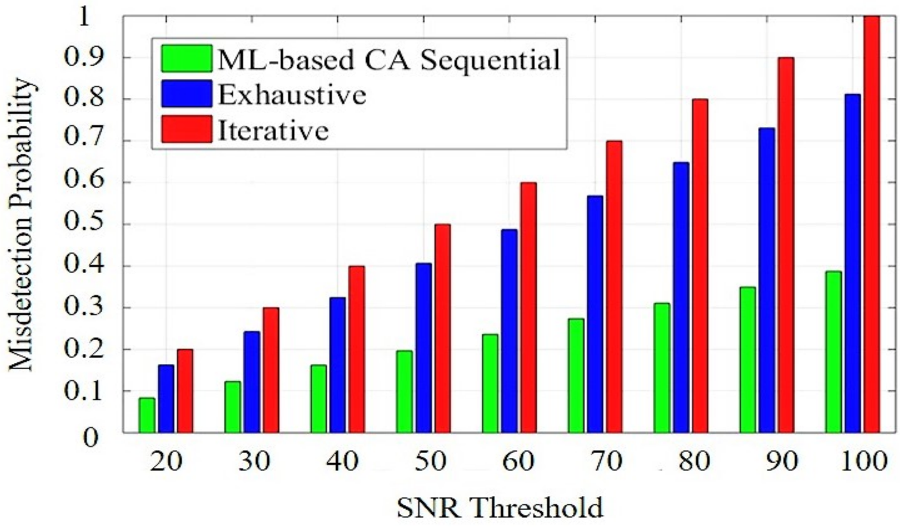

Figure 4.5: SNR Threshold (α_{th}) vs. Misdetection Probability

4.5 Signal-to-Noise Ratio Threshold

Exhaustive search always spans the 360^o area with 10^o beamwidth providing a larger range and gain to meet the SNR requirements even to the farthest premises of the cell, resultantly providing lower PMD as depicted by the bar graphs in Fig. 4.5. Iterative search spans the 360^o area in 5 stages, where beamwidth for stage 1 is 180^o, for stage 2 is 90^o, for stage 3 is 45^o, for stage 4 is 22.5^o and for stage 5 is 11.25^o. In each stage, algorithm spans only two sectors of the cell area. PMD is high for iterative search because firstly it searches the cell with larger sector area and beamwidth, i.e., shorter range thus missing the UEs on distant ends of the cell and also providing lower gains to meet the SNR requirements. Afterward, moving towards narrower bandwidths, although the gain and range are high but the sector area being searched is small.

Finally, the proposed algorithm makes use of available UE location to get

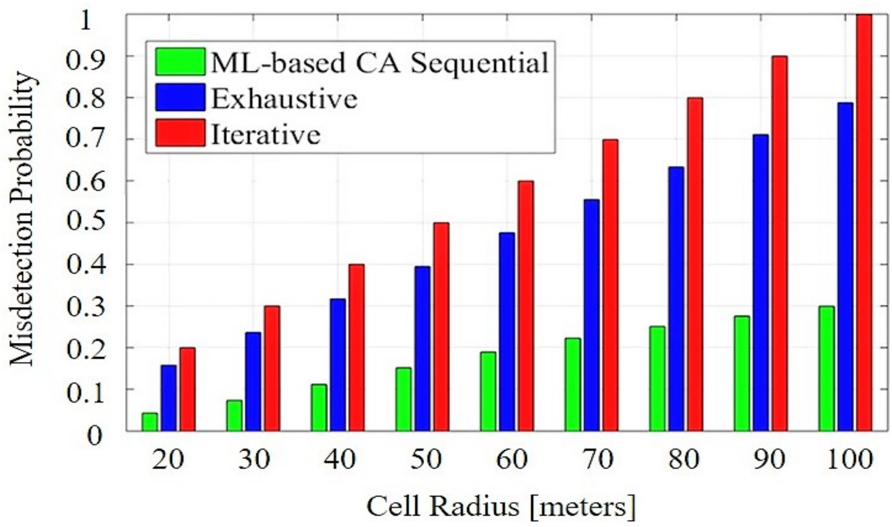

Figure 4.6: Cell Radius vs. Misdetection Probability

the most suitable beamwidth for connection and then directly points it to the given location. If due to certain factors, UE is not detected it searches the adjacent sectors to that location. Well, as ML-based CA sequential search devises the beamwidth and also the search sectors smartly, it offers lower PMD as compared to that of conventional algorithms.

4.6 Cell Radius

Small cell radius implies that UEs are in close vicinity of BS, hence small distance will result in high received power, meeting the SNR threshold criteria most of the time and giving low PMD. On the other hand, large cell radius allows UEs to spread on the area far from BS causing a low level of received power to satisfy the SNR requirements to the UEs located on distant premises and thus resulting in higher PMD.

Bar graphs in Fig. 4.6 analyze the effect of cell radius on exhaustive, iterative and ML-based CA sequential algorithms. As described, a smaller radius means lower PMD while larger radius causes an increase in PMD. Holistically, the proposed algorithm, owing to its smart design, provides a comparatively lower PMD.

Chapter 5

Conclusion and Future Work

In this dissertation, we familiarize the readers with the circumstances that lead to focus research in the mmWave frequency spectrum for 5G cellular communications. We overview the potential advantages that are gained by utilizing mmWave frquency band alongside discussing the hurdles in its deployment that suggest to devise new protocols and algorithms, especially the initial access in 5G mmWave communication systems, i.e., establishing the physical link between BS and UE to start formal communication, is a major concern and researchers are diligently working on developing efficient procedures for smart cell search. These studies can be categorized into sequential cell search and context aware cell search strategies and we have briefly discussed some search schemes related to the mentioned categories. We have developed a machine learning-based context aware sequential initial access algorithm for 5G mmWave communication systems that implements ML alongside CA to smartly search the cell area in order to connect to the UE. The algorithm's flow and performance analysis is summarized as follows:

1. In phase-1, the algorithm obtains contextual information in terms of UE and BS geo-locations, exploits ML using a probabilistic neural network (PNN) to suggest the best possible number of cell search sectors and beamwidth to establish the connection, keeping in view the UE mobility.

2. In phase-2, it sequentially searches the cell area to and forth the given location, to a certain limit, indicated by the probabilistic neural network output, to establish the connection.

3. Numerical simulations show that the proposed ML-based CA sequential algorithm has managed to offer a lower probability of misdetection alongside lower discovery delay during the IA phase as compared to those of traditional cell search algorithms, i.e., exhaustive and iterative schemes.

The proposed algorithm provides a perspective that can be considered in the future research studies. Currently, the algorithm utilizes only the BS and UE GPS coordinates to suggest suitable number of cell sectors and appropriate beamwidth for connection. We can enhance the availability and usage of contextual information in form of propagation environment alongside network, BS and UE characteristics to further improve the search duration and successful detection. Moreover, we can analyze the algorithm in terms of energy efficiency.

Bibliography

[1] Millimeter wave as the future of 5g. [Online]. Available: http://users.ece.utexas.edu/ rheath/presentations, 2015.

[2] M. Samimi, K. Wang, Y. Azar, G. Wong, R. Mayzus, H. Zhao, J. Schulz, S. Sun, F. Gutierrez, and T. Rappaport, "28 ghz angle of arrival and angle of departure analysis for outdoor cellular communications using steerable beam antennas in new york city," in *2013 IEEE 77th Vehicular Technology Conference, VTC Spring 2013 - Proceedings*, 2013.

[3] F. Devoti, I. Filippini, and A. Capone, "Mm-wave initial access: A context information overview," 06 2018, pp. 1–9.

[4] C. Barati, S. Hosseini, S. Rangan, P. Liu, T. Korakis, S. Panwar, and T. Rappaport, "Directional cell discovery in millimeter wave cellular networks," *IEEE Transactions on Wireless Communications*, vol. 14, no. 12, pp. 6664–6678, 12 2015.

[5] M. S. Corson, R. Laroia, J. Li, V. Park, T. Richardson, and G. Tsirtsis, "Toward proximity-aware internetworking," *IEEE Wireless Communications*, vol. 17, no. 6, pp. 26–33, December 2010.

[6] H. Viswanathan, K. Mun, F. Scholler, and A. Lucent, “Modeling and analysis of cellular wireless machine-to-machine communication traffic,” 03 2012.

[7] A. Mder, P. Rost, and D. Staehle, “The challenge of m2m communications for the cellular radio access network,” 01 2011.

[8] F. Xia, L. T. Yang, L. Wang, and A. Vinel, “Internet of things,” *Int. J. Commun. Syst.*, vol. 25, no. 9, pp. 1101–1102, Sep. 2012. [Online]. Available: http://dx.doi.org/10.1002/dac.2417

[9] R. I. Ansari, H. Pervaiz, C. Chrysostomou, S. A. Hassan, A. Mahmood, and M. Gidlund, “Control-data separation architecture for dual-band mmwave networks: A new dimension to spectrum management,” *IEEE Access*, vol. 7, pp. 34 925–34 937, 2019.

[10] H. Munir, H. Pervaiz, S. A. Hassan, L. Musavian, Q. Ni, M. A. Imran, and R. Tafazolli, “Computationally intelligent techniques for resource management in mmwave small cell networks,” *IEEE Wireless Communications*, vol. 25, no. 4, pp. 32–39, AUGUST 2018.

[11] S. A. R. Naqvi, H. Pervaiz, S. A. Hassan, L. Musavian, Q. Ni, M. A. Imran, X. Ge, and R. Tafazolli, “Energy-aware radio resource management in d2d-enabled multi-tier hetnets,” *IEEE Access*, vol. 6, pp. 16 610–16 622, 2018.

[12] H. Munir, S. Hassan, H. Pervaiz, Q. Ni, and L. Musavian, “Resource optimisation in multi-tier hetnets exploiting multi-slope path loss model,” *IEEE Access*, vol. PP, 05 2017.

[13] M. F. Kader and S. Shin, "Cooperative spectrum sharing with space time block coding and non-orthogonal multiple access," 07 2016, pp. 490–494.

[14] M. S. Omar, S. A. Hassan, H. Pervaiz, Q. Ni, L. Musavian, S. Mumtaz, and O. A. Dobre, "Multiobjective optimization in 5g hybrid networks," *IEEE Internet of Things Journal*, vol. 5, no. 3, pp. 1588–1597, June 2018.

[15] S. Qureshi, S. A. Hassan, and D. N. K. Jayakody, "Divide-and-allocate: An uplink successive bandwidth division noma system," *Transactions on Emerging Telecommunications Technologies*, vol. 29, no. 1, p. e3216, e3216 ett.3216. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/ett.3216

[16] R. I. Ansari, C. Chrysostomou, S. A. Hassan, M. Guizani, S. Mumtaz, J. Rodriguez, and J. J. P. C. Rodrigues, "5g d2d networks: Techniques, challenges, and future prospects," *IEEE Systems Journal*, vol. 12, no. 4, pp. 3970–3984, Dec 2018.

[17] S. Nawaz and S. Hassan, "Auxiliary beam pair enabled initial access in mmwave systems: Analysis and design insights," 05 2019.

[18] A. Riaz, S. Saleem, and S. Hassan, "Energy efficient neighbor discovery for mmwave d2d networks using polya's necklaces," 12 2018.

[19] O. W. Bhatti, H. Suhail, U. Akbar, S. A. Hassan, H. Pervaiz, L. Musavian, and Q. Ni, "Performance analysis of decoupled cell association

in multi-tier hybrid networks using real blockage environments," in *2017 13th International Wireless Communications and Mobile Computing Conference (IWCMC)*, June 2017, pp. 62–67.

[20] S. Habib, S. A. Hassan, A. A. Nasir, and H. Mehrpouyan, "Millimeter wave cell search for initial access: Analysis, design, and implementation," in *2017 13th International Wireless Communications and Mobile Computing Conference (IWCMC)*, June 2017, pp. 922–927.

[21] A. Umer, S. Hassan, H. Pervaiz, Q. Ni, and L. Musavian, "Coverage and rate analysis for massive mimo-enabled heterogeneous networks with millimeter wave small cells," 06 2017.

[22] S. A. R. Naqvi, S. A. Hassan, H. Pervaiz, Q. Ni, and L. Musavian, "Self-adaptive power control mechanism in d2d enabled hybrid cellular network with mmwave small cells: An optimization approach," in *2016 IEEE Globecom Workshops (GC Wkshps)*, Dec 2016, pp. 1–6.

[23] H. Munir, S. A. Hassan, H. Pervaiz, Q. Ni, and L. Musavian, "Energy efficient resource allocation in 5g hybrid heterogeneous networks: A game theoretic approach," in *2016 IEEE 84th Vehicular Technology Conference (VTC-Fall)*, Sep. 2016, pp. 1–5.

[24] S. A. R. Naqvi and S. A. Hassan, "Combining noma and mmwave technology for cellular communication," in *2016 IEEE 84th Vehicular Technology Conference (VTC-Fall)*, Sep. 2016, pp. 1–5.

[25] M. S. Omar, M. A. Anjum, S. A. Hassan, H. Pervaiz, and Q. Niv, "Performance analysis of hybrid 5g cellular networks exploiting mmwave

capabilities in suburban areas," in *2016 IEEE International Conference on Communications (ICC)*, May 2016, pp. 1–6.

[26] S. A. R. Naqvi, S. A. Hassan, and Z. ul Mulk, "Pilot reuse and sum rate analysis of mmwave and uhf-based massive mimo systems," in *2016 IEEE 83rd Vehicular Technology Conference (VTC Spring)*, May 2016, pp. 1–5.

[27] E-band technology. e-band communications. [Online]. Available: http://www.eband.com/index.php?id=86.

[28] R. J. Humpleman and P. A. Watson, "Investigation of attenuation by rainfall at 60 ghz," *Proceedings of the Institution of Electrical Engineers*, vol. 125, no. 2, pp. 85–91, February 1978.

[29] Z. Qingling and J. Li, "Rain attenuation in millimeter wave ranges," *2006 7th International Symposium on Antennas, Propagation EM Theory*, pp. 1–4, 2006.

[30] L. Wei, R. Hu, Y. Qian, and G. Wu, "Key elements to enable millimeter wave communications for 5g wireless systems," *IEEE Wireless Communications*, vol. 21, pp. 136–143, 12 2014.

[31] Y. Azar, G. Wong, K. Wang, R. Mayzus, J. Schulz, H. Zhao, F. Gutierrez, D. Hwang, and T. Rappaport, "28 ghz propagation measurements for outdoor cellular communications using steerable beam antennas in new york city," in *2013 IEEE International Conference on Communications, ICC 2013*, 2013, pp. 5143–5147.

[32] T. Bai, R. Vaze, and R. W. Heath, "Analysis of blockage effects on urban cellular networks," *IEEE Transactions on Wireless Communications*, vol. 13, no. 9, pp. 5070–5083, Sep. 2014.

[33] G. Maccartney and T. Rappaport, "73 ghz millimeter wave propagation measurements for outdoor urban mobile and backhaul communications in new york city," in *2014 IEEE International Conference on Communications, ICC 2014*. IEEE Computer Society, 2014, pp. 4862–4867.

[34] T. Rappaport, F. Gutierrez, E. Ben-Dor, J. Murdock, Y. Qiao, and J. Tamir, "Broadband millimeter-wave propagation measurements and models using adaptive-beam antennas for outdoor urban cellular communications," *IEEE Transactions on Antennas and Propagation*, vol. 61, no. 4, pp. 1850–1859, 2013.

[35] T. Rappaport, S. Sun, R. Mayzus, H. Zhao, Y. Azar, K. Wang, G. Wong, J. Schulz, M. Samimi, and F. Gutierrez, "Millimeter wave mobile communications for 5g cellular: It will work!" *IEEE Access*, vol. 1, pp. 335–349, 2013.

[36] S. Sun, G. Maccartney, M. Samimi, S. Nie, and T. Rappaport, "Millimeter wave multi-beam antenna combining for 5g cellular link improvement in new york city," in *2014 IEEE International Conference on Communications, ICC 2014*. IEEE Computer Society, 2014, pp. 5468–5473.

[37] H. Zhao, R. Mayzus, S. Sun, M. Samimi, J. Schulz, Y. Azar, K. Wang, G. Wong, F. Gutierrez, and T. Rappaport, "28 ghz millimeter wave cellular communication measurements for reflection and penetration loss

in and around buildings in new york city," in *2013 IEEE International Conference on Communications, ICC 2013*, 2013, pp. 5163–5167.

[38] W. Roh, J. Seol, J. Park, B. Lee, J. Lee, Y. Kim, J. Cho, K. Cheun, and F. Aryanfar, "Millimeter-wave beamforming as an enabling technology for 5g cellular communications: theoretical feasibility and prototype results," *IEEE Communications Magazine*, vol. 52, no. 2, pp. 106–113, February 2014.

[39] S. Sun, T. Rappaport, R. Heath, A. Nix, and S. Rangan, "Mimo for millimeter-wave wireless communications: Beamforming, spatial multiplexing, or both?" *IEEE Communications Magazine*, vol. 52, no. 12, pp. 110–121, 2014.

[40] R. J. Weiler, M. Peter, W. Keusgen, E. Calvanese-Strinati, A. De Domenico, I. Filippini, A. Capone, I. Siaud, A. Ulmer-Moll, A. Maltsev, T. Haustein, and K. Sakaguchi, "Enabling 5g backhaul and access with millimeter-waves," in *2014 European Conference on Networks and Communications (EuCNC)*, June 2014, pp. 1–5.

[41] K. Zheng, L. Zhao, J. Mei, M. Dohler, W. Xiang, and Y. Peng, "10 gb/s hetsnets with millimeter-wave communications: access and networking - challenges and protocols," *IEEE Communications Magazine*, vol. 53, no. 1, pp. 222–231, January 2015.

[42] C. N. Barati, S. A. Hosseini, S. Rangan, P. Liu, T. Korakis, S. S. Panwar, and T. S. Rappaport, "Directional cell discovery in millimeter wave

cellular networks," *IEEE Transactions on Wireless Communications*, vol. 14, no. 12, pp. 6664–6678, Dec 2015.

[43] Q. C. Li, H. Niu, G. Wu, and R. Q. Hu, "Anchor-booster based heterogeneous networks with mmwave capable booster cells," *2013 IEEE Globecom Workshops (GC Wkshps)*, pp. 93–98, 2013.

[44] T. S. Rappaport, R. W. Heath Jr, R. C. Daniels, and J. N. Murdock, *Millimeter wave wireless communications.* Pearson Education, 2014.

[45] R. R. Choudhury and N. H. Vaidya, "Deafness: a mac problem in ad hoc networks when using directional antennas," *Proceedings of the 12th IEEE International Conference on Network Protocols, 2004. ICNP 2004.*, pp. 283–292, 2004.

[46] H. Shokri-Ghadikolaei, C. Fischione, G. Fodor, P. Popovski, and M. Zorzi, "Millimeter wave cellular networks: A mac layer perspective," *IEEE Transactions on Communications*, vol. 63, no. 10, pp. 3437–3458, Oct 2015.

[47] "Ieee draft standard for information technology - telecommunications and information exchange between systems - local and metropolitan area networks - specific requirements - part 11: Wireless lan medium access control (mac) and physical layer (phy) specifications," *IEEE Draft P802.11-REVmb/D6.0, September 2010 (Revision of IEEE Std 802.11-2007, as amended by IEEE Std 802.11k-2008, IEEE Std 802.11r-2008, IEEE Std 802.11y-2008, IEEE Std 802.11w-2009 and IEEE Std 802.11n-2009)*, pp. 1–2097, Sep. 2010.

[48] Ieee 802.15 wpan task group 3c (tg3c) millimeter wave alternative phy. [Online]. Available: http://www.ieee802.org/15/pub/TG3c.html.

[49] H. Ajorloo and M. T. Manzuri-Shalmani, "Modeling beacon period length of the uwb and 60-ghz mmwave wpans based on ecma-368 and ecma-387 standards," *IEEE Transactions on Mobile Computing*, vol. 12, no. 6, pp. 1201–1213, June 2013.

[50] High rate. ghz phy, mac and hdmi pal, 2008.

[51] C. Jeong, J. Park, and H. Yu, "Random access in millimeter-wave beamforming cellular networks: issues and approaches," *IEEE Communications Magazine*, vol. 53, no. 1, pp. 180–185, January 2015.

[52] V. Desai, L. Krzymien, P. Sartori, W. Xiao, A. Soong, and A. Alkhateeb, "Initial beamforming for mmwave communications," in *2014 48th Asilomar Conference on Signals, Systems and Computers*, Nov 2014, pp. 1926–1930.

[53] M. Giordani, M. Mezzavilla, C. N. Barati, S. Rangan, and M. Zorzi, "Comparative analysis of initial access techniques in 5g mmwave cellular networks," in *2016 Annual Conference on Information Science and Systems (CISS)*, March 2016, pp. 268–273.

[54] T. Rappaport, *Wireless communications: Principles and practice.* Prentice Hall, 1996.

[55] A. Capone, I. Filippini, and V. Sciancalepore, "Context information for fast cell discovery in mm-wave 5g networks," in *Proceedings of European Wireless 2015; 21th European Wireless Conference*, May 2015, pp. 1–6.

[56] W. B. Abbas and M. Zorzi, "Context information based initial cell search for millimeter wave 5g cellular networks," in *2016 European Conference on Networks and Communications (EuCNC)*, June 2016, pp. 111–116.

[57] J. C. Aviles and A. Kouki, "Exploiting site-specific propagation characteristics in directional search at 28 ghz," *IEEE Access*, vol. 4, pp. 3894–3906, 2016.

[58] R. Parada and M. Zorzi, "Cell discovery based on historical user's location in mmwave 5g," in *European Wireless 2017; 23th European Wireless Conference*, May 2017, pp. 1–6.

[59] J. C. Aviles and A. Kouki, "Position-aided mm-wave beam training under nlos conditions," *IEEE Access*, vol. 4, pp. 8703–8714, 2016.

[60] U. M. Khan, Z. Kabir, S. A. Hassan, and S. H. Ahmed, "A deep learning framework using passive wifi sensing for respiration monitoring," *GLOBECOM 2017 - 2017 IEEE Global Communications Conference*, pp. 1–6, 2017.

[61] T. Bai and R. W. Heath, "Coverage and rate analysis for millimeter-wave cellular networks," *IEEE Transactions on Wireless Communications*, vol. 14, no. 2, pp. 1100–1114, Feb 2015.