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A Comprehensive Investigation of Beam Management Through Conventional and Deep Learning Approach

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Abstract—5G spectrum uses cutting-edge technology which delivers high data rates, low latency, increased capacity, and high spectrum utilization. To cater to these requirements various technologies are available such as Multiple Access Technology (MAT), Multiple Input Multiple Output technology (MIMO), Millimetre (mm) wave technology, Non-Orthogonal Multiple Access Technology (NOMA), Simultaneous Wireless Information and Power Transfer (SWIPT). Of all available technologies, mmWave is prominent as it provides favorable opportunities for 5G. Millimeter-wave is capable of providing a high data rate i.e., 10 Gbit/sec. Also, a tremendous amount of raw bandwidth is available i.e., around 250 GHz, which is an attractive characteristic of the mmWave band to relieve mobile data traffic congestion in the low frequency band. It has a high frequency i.e., 30 – 300 GHz, giving very high speed. It has a very short wavelength i.e., 1-10mm, because of this it provides the compact size of the component. It will provide a throughput of up to 20 Gbps. It has narrow beams and will increase security and reduce interference. When the main beam of the transmitter and receiver are not aligned properly there is a problem in ideal communication. To solve this problem beam management is one of the solutions to form a strong communication link between transmitter and receiver. This paper aims to address challenges in beam management and proposes a framework for realization. Towards the same, the paper initially introduces various challenges in beam management. Towards building an effective beam management system when a user is moving, various steps are present like beam selection, beam tracking, beam alignment, and beam forming. Hence the subsequent sections of the paper illustrate various beam management procedures in mmWave using conventional methods as well as using deep learning techniques. The paper also presents a case study on the framework's implementation using the above-mentioned techniques in mmWave communication. Also glimpses on future research directions are detailed in the final sections. Such beam management techniques when used for mmWave technology will enable build fast, efficient, and capable 5G networks..

Keywords-mmwave; beam management; CSI; beam tracking; beam training; beam selection; beam alignment; beamforming.

I. INTRODUCTION

The evolution of cellular communication from 1G to 5G is necessary with the increase in customers, traffic, and requirements. The enormous use of mobile data and spectrum shortage in the sub-6 GHz band is creating challenges to the current wireless networks. Towards the same, the millimeter-wave technology has various benefits that support its usage of mmwave as prominent technology in 5G. It has a high frequency i.e., 30 – 300 GHz that will give very high speed [1]. Also, it provides a very short wavelength ranging from 1-10mm, and hence tiny size components can be utilized in mmWave frequency. Further, a tremendous amount of raw bandwidth is available at this frequency band [2]. This will help relieve mobile data traffic congestion in the lower frequency band and provides a throughput of upto 20 Gbps. It has narrow bands as well as increased security and reduced interference.

Millimeter waves are susceptible to various propagation factors like atmospheric attenuation due to water and oxygen rain attenuation, free space loss, foliage attenuation, material penetration, and propagation mechanism such as refraction, diffraction, multipath, scattering, and reflection [2]. When the main beam of the transmitter and receiver are not aligned properly there is a problem in ideal communication. To solve this problem beam management is one of the solutions to form a strong communication link between transmitter and receiver. Beam management is used to provide fine alignment between the transmitter and receiver beam [4].

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This paper focuses on a specific design namely beam management in mmWave. Beam management includes multiple procedures which select suitable antenna beams to transmit and receive radio signals.

Beam adjustment between both ends is necessary when the user is moving to ensure increased gain in beamforming. Beam management is fundamental in performing various tasks such as channel state information, beam tracking, beam training, beam alignment, and beamforming.

Channel State Information (CSI): CSI refers to known channel properties of radio link and gives combined effect of path loss, scattering, diffraction, fading, shadowing, etc., when propagating signals from a transmitter to its corresponding receiver via the air. Usually, CSI information is used to quantify the quality of a radio link [5].

Beam Training: The beam training in mmWave channel is used to find the best beam pair suited for transmission to avoid the estimation of large dimensions [6].

Beam Selection: The beam selection is finding a few beams out of all beams to form a strong communication path between the user and mobile user [7].

Beam Alignment: The main purpose of channel estimation is to find the location of one strong connecting user and base station. The beam alignment is used to find this strong communication link [8].

Beamforming: High path loss at a higher frequency is challenge in mmWave technology. Towards the same directional beamforming is required, which helps improve antenna gain at the user and base station using multiple antennae. This technique is called beamforming where a narrow beam is formed by adjusting the phase/amplitude of an antenna [8].

Beam Management: Beam management is the process of controlling and optimizing the directionality of the radio signal transmitted between the transmitting and receiving antennas.

The overall beam management consists of all the elements which have been given in fig. 1.1.

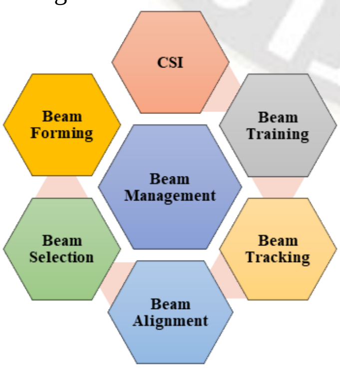

Fig. 1.1: Beam Management Process

Although beam management is strong enabler in millimeter wave technology there are some challenges in its implementation as shown in table I.

TABLE I CHALLENGES IN BEAM MANAGEMENT

References	Challenges
[3]	Pathloss
[4]	Blockage
[10]	Shadowing
[50]	High beamforming complexity
	Interference Management
[60]	Limited channel information

This paper tries to attempts in identifying future research direction towards addressing the challenges listed above.

The contributions of the paper are as follows.

- To perform comprehensive study of beam management using conventional techniques.
- To carry out complete overview of beam management using deep learning approach.
- To present a case study towards accomplishing beam management in millimeter wave communication.
- To give insight on future research directions based on identified challenges in beam management.

The organization of paper is as shown in fig. 1.2.

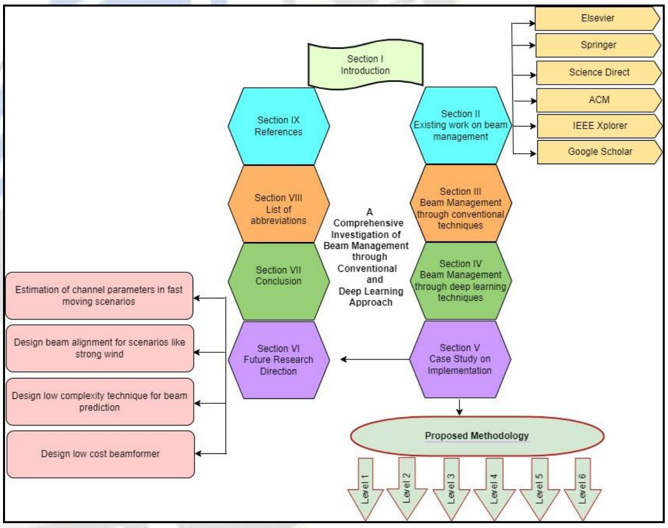

Fig. 1.2: Organization of paper

II. EXISTING WORK ON BEAM MANAGEMENT

Over the past decades, various studies were conducted on beam management using the conventional method as well as deep learning methods. The main intent of this section is to include a comprehensive literature study of beam management techniques. Fig. 2.1(a) gives the distribution of research documents from IEEE Xplore digital library and fig. 2.1(b) gives the distribution as per journal and conference papers from IEEE Xplore digital library.

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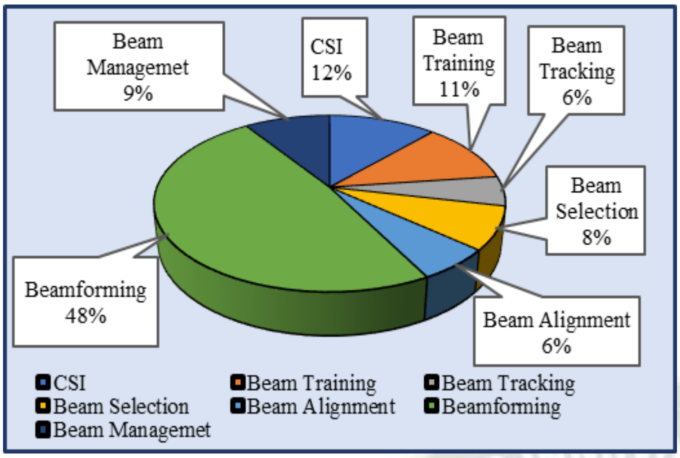
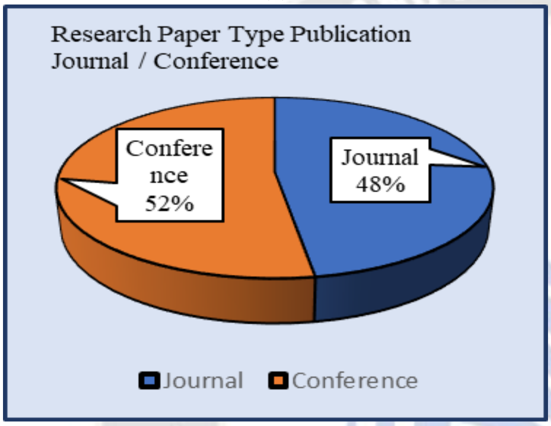


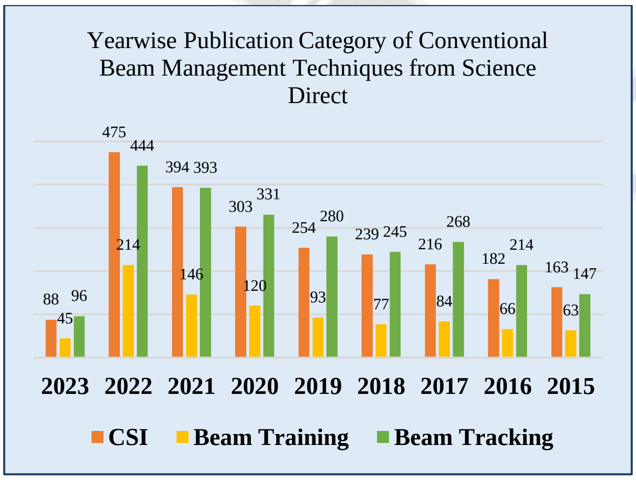
(a)



(b)

Fig. 2.1(a), (b): Distribution of Research Documents from IEEE Xplore

From the above figure, it is observed that only 9% of work is done in beam management leading to tremendous scope for future study. Also, it is observed that research in beam tracking, beam selection and beam alignment have been unexplored using deep learning techniques.



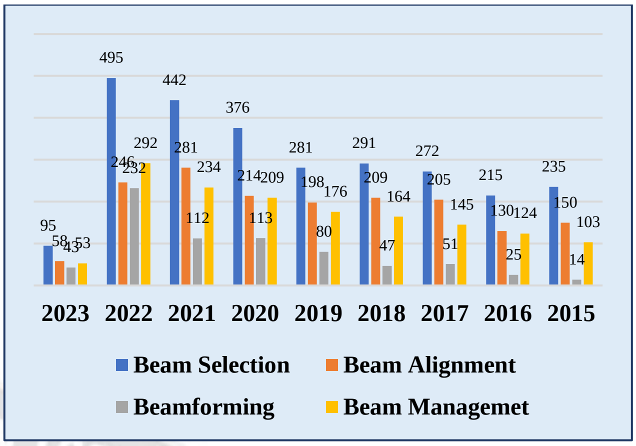


Fig. 2.2: Year wise publication of beam management techniques from Science Direct

Fig.2.2 depicts yearwise summary of publication encompassing various techniques involved in beam management techniques. This database is collected from Science Direct repository.

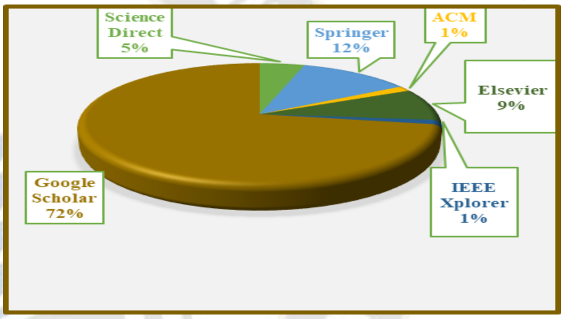


Fig. 2.3: Distribution of papers according to publishers

Fig. 2.3 gives the distribution of research papers according to various repositories like Elsevier, Science Direct, Springer, ACM, IEEE Xplore, and Google scholar.

To identify various advancement in beam management, various databases including Science Direct, Elsevier, Springer, Web of Science (WoS), ACM (Association for Computing Machinery), Google Scholar, Scopus, and IEEE Xplore were analysed. The title field was searched in databases using search words "CSI," "Beam training & Tracking," Beam selection," "Beam alignment", and "Beam management in millimeter wave". The search strings along with databases are shown in table II.

TABLE III A DATABASE SPECIFIC SEARCH STRING

Sr. No.	Database	Search Keyword
1	Google Scholar	**Title:** "CSI in millimeter wave communication", "beam training in mmwave", "beam selection in mmwave", "beam management in mmwave"
2	Scopus	**Title:** "Beam Management in Millimeter Wave", "Beamforming in Millimeter Wave", "Beam Alignment in Millimeter Wave", "Channel State Estimation in Millimeter Wave", "Beam Tracking In Millimeter Wave", "Beam Training In Millimeter Wave", "Beam Selection In Millimeter Wave"

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The network, overlay, and density visualization analysis for various authors who have published in domain of beam management has been analysed and presented in figure 2.4 a, b, and c to comprehend the depth of work in the above-mentioned area.

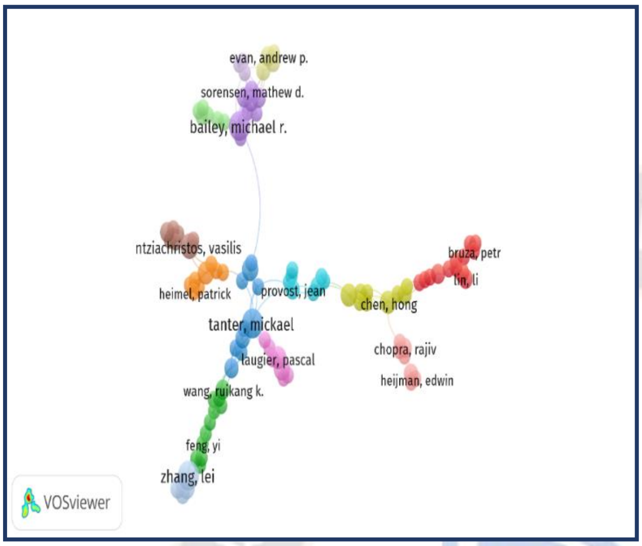
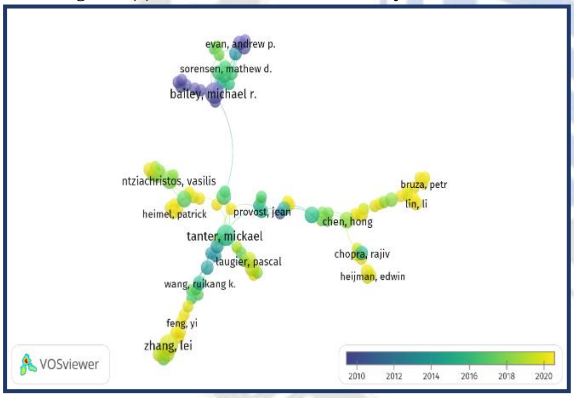
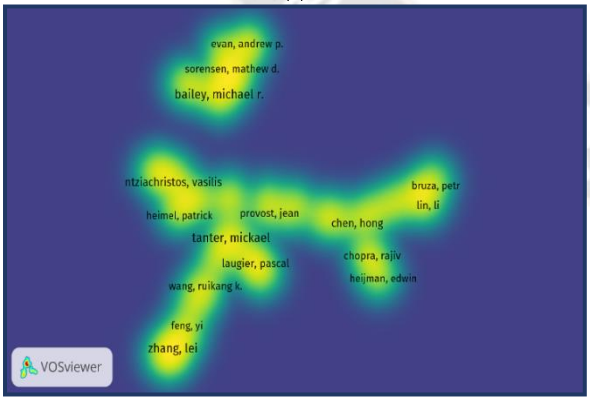


Fig. 2.4 (a): Network visualization analysis for author



(b)



(c)

Fig. 2.4: (b) Overlay and (c) Density visualization analysis for the author search

A visual representation of the citations of different authors over the years in the domain of beam management is shown in fig. 2.5. Every unique author name is represented by a circle.

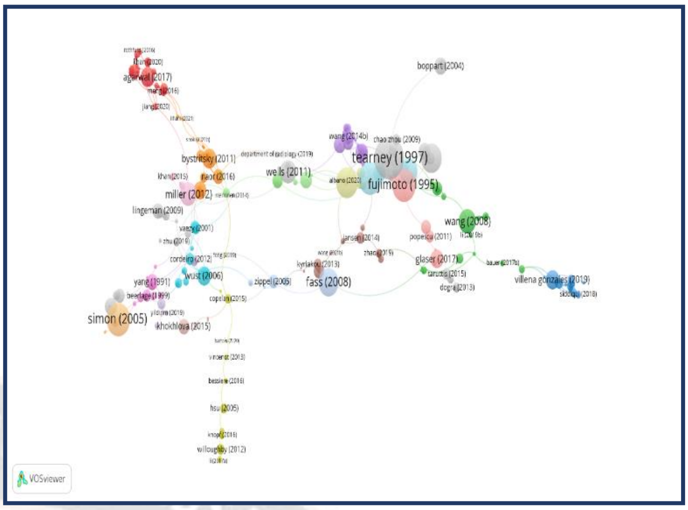


Fig. 2.5: Network visualization analysis for citations

III. BEAM MANAGEMENT THROUGH CONVENTIONAL TECHNIQUES

To provide high data requirements for the next generation, the millimeter wave is one of the prominent technologies because of its high bandwidth. At higher frequencies, various losses are found like path loss, propagation loss, etc. All of these require proper beam management techniques to utilize the advantage of the mmWave band. Beam management can be performed using various techniques as follows

3.1 Channel State Information
3.2 Beam Training and Tracking
3.3 Beam Selection
3.4 Beam Alignment
3.5 Beamforming

3.1 Channel State Information

Conventionally, CSI can be accomplished by using different algorithms. Different parameters which are associated with these algorithms are Achievable Spectral Efficiency (ASE), Normalised Mean Square Error (NMSE), and Convergence along with SNR. Table III compares ASE and NMSE with different SNR values for different algorithms.

TABLE IIIII COMPARISON OF SNR, ASE AND NMSE WITH A DIFFERENT ALGORITHM

Paper	Algorithm	SNR	ASE	NMSE
[9], [10]	orthogonal matching pursuit (OMP)	At low-to-mid SNR	Moderate	Constant
		At moderately high SNR (T<400)	Worse	Not capable to recover
	Two-stage sparse representation (TSSR)	At every SNR point	Very bad	Not capable of recovering estimated values

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	Vector approximate message passing (VAMP)	At smaller training symbol	Very poor (T<400)	Very poor (T<800)
		At training symbol length increases	Performance increases (at T > 400)	Performance increases (at T > 800)
	Alternating Direction Method of Multipliers (ADMM)	For every SNR, for all training symbol lengths than another algorithm	Perform better	Better performance
	Ex-ADMM algorithm	For T=400, at all SNR point	Perform better than all other algorithms	Better performance
		For medium SNR (T = 800 & 1200)	ADMM & Ex-ADMM perform simultaneously	--
		At mid-to-high SNR	perform better than ADMM	--
		For high training symbol length	Very close to achieving perfect CSI	--

Among all the above algorithms in table III it is observed that the Ex-ADMM algorithm has a very high achievement rate i.e., it is close to achieving perfect CSI for high training symbol length. Also, it is observed that Two-Stage Sparse Representation (TSSR) has a very poor achievable rate at every point of SNR. Further, it is observed that ADMM can exploit the low rank and sparsity of any channel matrix individually at any training symbol length. However, TSSR is not capable of recovering estimated values at low and high training symbol lengths.

3.2 Beam Tracking / Beam Training

Beam tracking is used to transmit known symbols selected beams and to track time-varying channels for maintaining a good communication link. When the user is moving it is expected that the mmWave channel also varies fast, which hampers ideal communication. To solve this problem, a model that captures the changing behavior of the mmWave channel is required. There are different techniques by which beam tracking can be accomplished. Below table IV lists all the techniques and gives details of all the techniques.

TABLE IVV COMPARISON SURVEY OF DIFFERENT BEAM TRACKING TECHNIQUES

Paper	Technique	Detail
[11], [12], [13],	Fast beam training algorithm using the codebook	• Reduce training overhead
[14], [15]	Sub-array structure with directional antenna elements and phase shifters	• Improve degrees of freedom (EDoF) to get more multiplexing gain
	Local Maximum Likelihood (LML)	• Estimate parameter of received signal based on received data then used estimated parameter to predict next samples of received signal

From above Table IV, it is observed that a fast beam training algorithm based on the codebook is used to reduce the number of trainings for the designed mmWave system.

3.3 Beam Selection

Beam selection is effective to get high beamforming gain with low overhead & latency of initial access in millimeter-wave communication. The beam selection can be done through various techniques as shown in Table V.

TABLE V BEAM SELECTION TECHNIQUE AND DETAILS

Paper	Technique	Details
[16], [17], [18], [19], [20]	decentralized beam selection algorithm	• Central unit is not required for beam selection
	Hierarchical Beam Search	• Reduce space search space of Beam Alignment • Deduced accuracy because of reduction in gain of antenna & inadequate spatial resolution with large beam width which affect search procedure
	Joint beam and user selection	• Find proper subset of user and beams • Improve system sum rate

Out of all the different techniques available for beam selection, it is observed that the code book-based beam selection technique is used to reduce complexity and for RF implementation of the beamformer. Also, to construct beams in the codebook analog and digital beamforming can be used. Hierarchical Beam Search is used when there is a need to reduce space search.

3.4 Beam Alignment

The higher data rate requirement is fulfilled by mmWave because of larger bandwidth, beamforming, and spatial multiplexing. Due to free space path loss available at higher frequencies, communication at mmWave is challenging. To overcome this challenge, directional beamforming with a massive number of antennas is one of the solutions.
Beam alignment techniques are listed in Table VI.

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TABLE VI BEAM ALIGNMENT TECHNIQUE WITH DESCRIPTION

Paper	Technique	Details
[21], [22], [23], [24], [25]	Exhaustive search Algorithm	• Used to get the best beam pair • High delay complexity
	Hierarchical Codebook Adaptive Algorithm	• Reduced delay present in Exhaustive search Algorithm • Jointly search over channel subspace
	Beam pre-selection Algorithm	• Beam selection speed gets increased • Since beam selection is based on information about noisy locations, performance is not definite
	Decentralized Beam Selection	• Reduce the performance of the system

From all techniques introduced in Table VI it is observed that exhaustive search algorithm is used to find the pair of best beams however this algorithm has high delay complexity. To solve this delay complexity Hierarchical Codebook Adaptive Algorithm can be used. It is also seen that the decentralized beam selection method degrades system performance.

3.5 Beamforming

To provide a better user experience, 5G focuses on mmWave communication along with its key technology i.e., Beamforming. For high gain, beamforming is applied at both transmitters as well as at the receiver.

TABLE VII TYPE OF BEAMFORMING

Parameter	Analog Beamforming	Digital Beamforming	Hybrid Beamforming
Flexibility	Low	High	High
Performance	Better	Best	Improved
Hardware Cost	Low	High	Low

Table VII depicts the variation in parameters depending on the type of beamforming. From the above table, it is observed that hybrid beamforming is very popular because of improved performance along with low hardware cost and high flexibility.

IV. BEAM MANAGEMENT THROUGH DEEP LEARNING TECHNIQUES

Initially beam management was approached through conventional methods. However, over the period deep learning techniques have gained popularity to accomplish beam management towards improvement in performance parameter. This section presents a survey of different deep learning techniques being used for different stages of beam management.

4.1 Channel State Information

TABLE VIII SURVEY OF CHANNEL ESTIMATION USING DEEP LEARNING TECHNIQUE

Paper	Parameter Predicted	Benchmark for Parameter Prediction	DL Model	Hyper Parameter	Performance Metrics	Salient Features of Developed Model
[26]	Channel estimation	• Estimation accuracy • Spectrum efficiency	Convolutional Neural Network	• Learning rate = 10^{-4} • Penalty area δ = 0.005 • N_f= 16 feature map • Carrier frequency fc = 30 GHz • N_t = N_r = 64 antennas at transmitter and receiver • Length of OFDM data block length N = 4096 • Length of CP M = 256 • Max. channel length set L = 256 = CP length • Feature map size = 32*32 • Mini batch size = 64 • Convolution kernel size = 5*5 • Stride = 1 • ReLU • Adam optimizer	Normalized Mean Square Error	• Require less pilots for channel estimation • Save subcarrier resource
[27]	CSI prediction	• Efficiency • Accuracy • Effectiveness	Convolution Neural Network & Long Short-Term Memory	• 2*2 filter for 2D CNN • 3*1 filter for 1D CNN • 64 nodes • Update period 5 min • β = 0.1 • Stride through image	• Mean Square Error 0.551 • ADR (Average Difference Ratio) = 2.730 • System loss	• improve stability in practical • lowest computing time • low ADR • CSI prediction upto 2.650-3.457%

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[28]	Mmwave beam discovery	• measurement overhead • accuracy of path discovery • quality of estimated path gains • impact of channel estimation on achievable data rate	Deep Neural Network	• syndrome source code with generator matrices G_t & G_r = 5*31 & 4*51 size • number of antennas at transmitter m_t = 5 • number of antennas at receiver m_r = 4	• Mean Square Error • Probability of path misdetection • 95% reduction in measurement • avg search time required = 47	• Consumed Energy E_T increases • performance improves perfect channel discovery • Reduced number of measurements required for channel discovery
[29]	SNR prediction	• Performance of system • Communication quality	Convolutional Neural Network, Long Short-Term Memory, Deep Neural Network	• input is raw received signal • output is future channel characteristics • modulation mode = π / 2 QPSK • symbol rate (Msym/s) = 1760 • Carrier frequency = 62.5 GHz • Number of multipath = 2 • Vehicle speed = 320 Km/h • Maximum doppler shift = 18.5 KHz • Training environment python 3.6.10, tensorflow-gpu 1.13.1 • LSTM dropout = 0.3 • CNN kernel size = 3*3 • Adam optimizer • Time step N = 30 • Truncated length L = 3328 symbol	• Mean Square Error • Signal to Noise Ratio • Normalized Mean Square Error	• Improve efficiency and throughput • Better performance without payload cost of pilot • Improve communication quality
[30]	Channel Tracking	• Beam coherence time • Data rate • Channel estimation	Deep Neural Network, Long Short-Term Memory	• Adam optimizer • Learning rate 0.001 • Dropout 0.9 • Regularization = l_2 • Max. number of epochs 100 • Data size 50000 • Dataset split is 80:20	Normalized Mean Square Error •	• Negligible training overhead • Estimate & track mmwave channel efficiently
[31]	Channel estimation	• spectral efficiency • channel estimation • performance of system	Neural network	• Multiuser system • Number of RF chain at base station N_R = 4 • Number of antennas at base station N_A = 64 antennas • 3 users with single antenna • G = 128 • Number of multipath sets is 2 • Number of phase shifter at BS, B = 4 • Q = 16 • η = 100 • K = 8 time slot	• Normalized Mean Square Error • Signal to noise ratio	• Low resolution of phase shifter • High Spectral efficiency • Better channel estimation performance
[32]	Channel estimation, Symbol detection	• Training pilots • spectrum utilization	Deep Neural Network	• OFDM system • 64 sub-carrier • CP length = 16 • Carrier frequency = 2.6 GHz • Number of paths = 24 • Channel = Urban • Maximum delay = 16 • Modulation mode = QPSK • Pilots used = 8	• Bit error rate (BERs)	More Robustness to • number of pilots used for channel estimation • nonlinear clipping noise • Better spectrum utilization • Reduce BER with increasing SNR
[33]	channel estimation	• Pilot required complexity • performance of system • estimation performance	Deep Convolutional Neural Network	• corrupted channel matrices as input at adjacent subcarriers • number of antennas at transmitter N_T = 32 • number of antennas at receiver N_R = 16 • number of RF chains at transmitter & receiver = 2 • number of antenna at transmitter M_T = 32 • number of antenna at receiver M_R = 16	Minimum Mean Square Error	• robust to different propagation scenarios • requires one third of special pilot overhead at cost of complexity

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				• Carrier frequency Fc = 28 GHz • Sampling rate f_s = 100 MHz • Number of main paths L = 3 • Number of subcarriers K = 64 • Training set samples 81000 • Validation set sample size 9000 • Testing set sample size 19000 • Adam optimizer • Epochs set 800 • Learning rate = ➢ 10^{-4} for first 200 epochs ➢ $5 * 10^{-5}$ for next 400epochs ➢ 10^{-5} for last 200 epochs • Batch size128 • Scaling constant c = 2		• reduce pilot • reduced complexity • achieves performance closed to ideal MMSE estimator • improve estimation performance
[34]	uplink channel estimation	• system performance • channel estimation • feedback performance	Neural Network	• TDD system • Number of antennae at base station N_{BS} = 256 • Number of antennae at RF N_{RF} = 4 RF chains • Number of OFDM subcarriers in channel estimation phase K = 64 • Quantized angle grids G = 1024 • Training environment python 3.6, tensorflow-gpu 1.13.1 • T = 5 layers • Training set S_{tr} = 5000 samples • Validation set parameter S_{va}= 2000 • Test set parameter S_{te} = 1000	Normalized Mean Square Error	• Channel feedback overhead reduced • Enhance performance • Significant improvement in channel estimation & feedback performance
[35]	Channel estimation	• system performance • number of RF chains • training overhead	Convolutional Neural Network, Deep Denoising Neural Network	• UE equipped with 1 antenna • Carrier frequency 28 GHZ • Bandwidth f_{BW}= 100 MHZ • Number of OFDM subcarrier k = 256 • maximum multipath delay τ_{max}= 32 / f_{BW} • Cyclic prefix CP set L_{CP} = 32 • Number of path L = 6 • M = 64 active antennas • SOMP oversampling rate (β) 4 • Adam optimizer • 5000 training samples • Epochs 150 • Batch size 8 • Learning rate l_r= $1 * 10^{-4}$	• Normalized Mean Square Error	• Improve coverage and throughput • Improve accuracy • Richer representation capacities beyond real valued • Superior performance • Very few RF chains • Low training overhead • Robustness makes model applicable in different SNR scenario without repetitive training

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4.2 Beam Training and Beam Tracking

TABLE IX SURVEY OF BEAM TRAINING TECHNIQUE USING DEEP LEARNING

Paper	Parameter Predicted	Benchmark for Parameter Prediction	DL Model	Hyper Parameter	Performance Metrics	Salient Features of Developed Model
[36]	Narrow beam prediction	• User mobility • Beam prediction overhead • Spectral efficiency • Beamforming gain • beamwidth • Calibration of beam direction • Channel power leakage	Convolutional Neural Network, Long Short-Term Memory	• Carrier frequency fc = 28 GHz • Bandwidth W = 2 MHz • numbers of far scatterers n_g = 15 • Path number within one cluster Lc = 20 • Visible region radius rv = 40m • AoD spread within one cluster Δϕc = 2.40 • Delay spread within one cluster Δτc = 5 ns • Shadow fading standard deviation σSF = 4dB • Ricean K factor KR = 8dB • BS antenna number MTx = 64 • BS wide beam number NTx / sTx = 16 • BS narrow beam number NTx = 64 • Beam training period τ = 100 ms • Total beam training number T = 10 • Cell radius r = 100m • Transmit power P = 15dBm	• Tracking accuracy • Overhead	• Higher beamforming gain with reduced beam training overhead • Narrow beam prediction overhead reduction
[37]	Beam training	• Channel power leakage • channel path • signal coverage •	Deep Neural Network	• Three resolvable paths L = 3,10,14 • Number of hidden layer NL = 5 • Number of units in hidden layer 1000, 600, 300, 200, 100 • Number of channel matrices Hs in training dataset S = 1000000 • Epochs 100 • Batch size 1000 • Learning rate 0.01 • Base station antennas, N_A = 32 • User equipped with M_A = 1 antenna • Number of codewords in Wc & Fc = 32 & 1 • Beam training test I = 32 • Number of combinations for DNN, T = 15 • Number of additional beam training test K 32	• Successful rate • Achievable rate • training overhead • Signal to Noise Ratio	• Strongest channel path • Satisfactory performance in successful rate • Reduced beam training overhead • Better signal coverage
[38]	Training candidate beam	• Beam alignment accuracy •	Q-based Reinforcement Learning	• Coverage 10m * 10m • Carrier frequency 60 GHz • Noise power spectral density -170 dBm/Hz • System bandwidth B = 2.16 GHz • BI time TBI = 10ms • SSW, FB, ACK time TSSW, TFB, TACK = 15us, 15us, 15us • IFS time TSBIFS, TSIFS, TMBIFS = 1us, 3us, 9us • Number of Bis T = 100000 • UE moving speed 2 m/s • Number of beam sectors N = 16, 32, 64, 128, 256 • Ratio α of number of CNN inputs to N = 0.1, 0.2, 0.3, 0.4, 0.5	• Training latency • System throughput • overhead •	• User mobility • real-time performance with Gbps transmission throughput and millisecond level • training overhead
[39]	Beam measurement	• energy efficiency • spectral efficiency data rate	Deep Reinforcement Learning	• MATLAB R2021b platform with 3.1 GHz Dual-Core Intel Core i5 • T′ = 99 steps/samples in training phase • UE speed within cell v = 1 m/s • SNR allocated between 0 to 20 DB • state vector st contains T = 5 past measurement • BS antenna array = 8-by-8 URA • UE antenna array = 4-by-4 URA • Carrier frequency 30 GHz • No. of subcarriers N = 64 • No. of NLOS clusters L = 20 • No. of tracked beam pairs x = 3 • Channel bandwidth B = 100 MHz	• Signal to noise Ratio • Beamwidth	• Energy efficiency with 20% of reduced beam measurement • User mobility • High spectral efficiency with 10% saving on required beam measurement

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				• Noise variance $\sigma 2$ = n 0.1 • DRL learning rate η 0.001 • DRL discount factor $\gamma = 0.9$ • No. of DRL training episodes = 500–2000 • MAB step-size $\eta' = 0.5$ • DRL/MAB exploration factor $\varrho = 0.1$ • DRL mini-batch size 64 • Length of DRL experience buffer D = 100,000 • UE velocity v = 1 m/s		
[40]	Accurate beam alignment	Spectral efficiency	Deep Reinforcement Learning	• BS antenna configuration 8-by-8 URA • UE antenna configuration 4-by-4 URA • No. of subcarriers N = 64 • Carrier frequency 30 GHz • SNR 0 dB • No. of NLOS clusters L = 20 • No. of scatterers per cluster M = 20 • Discount factor 0.9 • Learning rate 0.001 • No. of training episodes 1000 to 2000 • Exploration factor 0.1	• Beam switching latency • Tracking stability	• High data rate with minimum amount of beam training • Beam search by saving 92.2% on required beam training overhead • Tracking dynamic mmwave channel • Change in environment
[41]	Beam prediction	• Mean accuracy System performance	Convolution Neural Network	• Dual mode wireless system • Distance between BS & UE ranges from 20m to 300m • LoS propagation environment • size of candidate transmitting beams is $N_{BS} = 8$ • sampling rate is 30.72MHz • subcarrier interval is 15kHz • LTE antenna number of BS is fixed as MTX = 8 • SNR ranges from 0dB to 20dB • MATLAB WINNER II toolbox • training set constructed with 81,920 samples • validation set with 20,480 samples • Adam optimizer	• Prediction accuracy • Signal to noise ratio • Training overhead	• High prediction accuracy • Robustness to SNR • Adaptivity to various CSI matrix size • 94% accuracy in LoS scenarios, which can reduce the overhead of beam training
[42]	Beam training	• sum rate Data rate	Deep Reinforcement Learning	• size of DFT codebook F is M = N	• Environment sensing rate • Training overhead • Training accuracy	• Beam training design from the perspective of environment sensing • Can apply to complicated scenarios • Reduce beam training overhead • Capture dynamic special pattern of environment • Average effective achievable sum rate

From above table IX it is observed that high beamforming gain leads to small beam training overhead. As the training period increases spectral efficiency also increases and larger power can be accumulated. For the better signal coverage there should be reduction in beam training overhead. There exists a trade-off between beam training accuracy and latency for maximizing throughput. Although the training latency increases as trade-off factor α and number of subcarrier N increase, higher accuracy from extracted information in the CNN and larger beam gains can result in higher throughput.

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TABLE X Survey of Beam Tracking Technique Using Deep Learning Techniques

Paper	Parameter Predicted	Benchmark for Parameter Prediction	DL Model	Hyper Parameter	Performance Metrics	Salient Features of Developed Model
[43]	beam tracking	• sum-rate • overhead • interference cancellation	Q-learning based model	• operating frequency is fc = 28 GHz • U = 2 MSs and BS • antenna spacing dtx= drx= λ/2 • number of antennas N = M = 32 • discount factor qDF= 0.5 • learning rate qLR= 0.5 • number of time steps for Phase 1 is TC = 8 • number of time steps for Phase 2 is TH = 12 • additional beam searching D = 3	• accuracy • signal to noise ratio	• higher effective sum-rate • low overhead • high-resolution beam tracking for practical environment • 54% improvement of achievable sum-rate over the baseline schemes at SNR 20 dB
[44]	AoA & AoD in terms of azimuth & elevation	• Absolute error • System performance	Deep Neural Network	• 1028 Input nodes • ReLU activation function • Output = 4 nodes • Transmit power 43 dBm • Carrier frequency 30 GHz • Noise -88 dBm • Effective bandwidth 200 MHz • Tx height 40m • Area length X = 223m • Area width Y = 328m • Number of grid position N = 73696	• Training accuracy • Angle of departure •	• Absolute error between real & predicted is quite low • Good performance when error is below threshold of 7^0 • Prediction error of AoA & AoD maintain within acceptable range of -2^0 to $+2^0$
[45]	Beam tracking	• Beam misalignment	Deep Reinforcement Learning	• Distance between endpoints d_w= 10m • Distance between wire & buildings d_r= 5m • Transmit power P_{TX} = 23 dBm • Wavelength of radio waves λ = 5mm • Received antenna gain G_{RX} = 8 dBi • Gravitational acceleration g = [0, 0, -9.8] ms^{-2} • Drag constant c_o = 1 s^{-1} • Number of points N = 21 • Mass of wire m = 10kg • Covariance matrix of wind speed V_o = 0.1 I • Number of vertical elements n_V= 32 • Number of horizontal elements n_h= 8 • Correlation coefficient ρ = 1 • Vertical spacing distance Δ_V = 2.5 mm • Horizontal spacing distance Δ_H = 2.5 mm • Point installed on-wire node = P10 • Interval between successive time instant τ =10ms • Refinement angles A = 1^0	Accuracy •	• Tracking feasibility • Learn relationship between historical positions / velocities & appropriate beam steering angels • Avoid beam misalignment
[46]	Beam prediction	• System performance • Data rate	Deep learning	• Adam optimizer • learning rate 0.001 • batch size 1000 • GRU layers 4 • GRU hidden layer dimension 256	• Loss function • Cross entropy loss	• proper use of image for better beam prediction

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				• epoch number 12 (for bi-GRU) and 50 (for bi-GRU) • dropout rate 0.2 • loss function = cross entropy loss	• Tracking accuracy	• improves beam prediction in NLoS environment
[47]	Beam Tracking	• beamforming gain • Precision • System performance •	Deep Neural Network, Long Short-Term Memory	• Mini batch size 64 • Initial learning rate 0.01 • Decay epoch 3 • Decay rate 0.1 • Total epoch 30 • Adam optimizer	• Tracking Accuracy • Angle of departure	• Significant performance gain over EKF baseline and outperformed the existing methods, especially in high mobility scenarios • Track fast varying AoD and AoA due
[48]	Wireless beam tracking	• beam prediction •	Long Short-Term Memory	• PyTorch environment using one NVIDIA 1060 6GB GPU • Training dataset D_t of 281100 user instances • Validation dataset D_v of 120468 user instances • Testing dataset D_{test} of 10000 user instances • 8 pair of the beam indices	• Tracking accuracy •	• Future beam sequence prediction • leveraging both wireless and visual data for beam prediction • beam predictions by previously observed beam indices and images using different feature extraction techniques

From above survey table X, it is observed that for beam tracking various deep learning techniques are available such as deep neural network, LSTM, deep reinforcement learning and Q-learning. Out of all these available techniques, q-learning technique gives 54% of improvement in sum rate. Also, these techniques can be used for beam tracking in fast varying environment also for tracking application.

4.3 Beam Selection

TABLE XI SURVEY OF BEAM SELECTION USING DEEP LEARNING TECHNIQUES

Paper	Parameter Predicted	Benchmark for Parameter Prediction	DL Model	Hyper Parameter	Performance Metrics	Salient Features of Developed Model
[49]	• Beam misalignment • Beam position	• Spectral efficiency • Latency • System performance	Deep Neural Network	• LR dimensions are 7m ×7m ×3m (W× L× H). • Two sofas, a table, and an armchair are placed in the LR • cabinet is placed between two windows of one of the outer walls • AP is placed in the middle of one of the LR walls • UT can take a position in a sector with the same height as the AP • sector has dimensions of 4m ×7m (W× L) • 70, 000 UT positions in the user sector • cluster blockage model • antenna array size {Nh = 4, Nv = 4} • model parameter set to 0 or 1 • Altair Feko-Winprop software • 25 strongest	• Blockage probability • Sensitivity • Precision	• misalignment probability • spectral efficiency (ESE) latency • High robustness to different line-of-sight blockage probability • lower sensitivity to inaccuracies in the position and orientation information • excellent performance when enough training samples • low sensitivity to changes in the propagation

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				multipath components at any UT position • Transmit power PAP = 0 dBm • Noise variance = -84 dBm • 80% training data and 20% test samples • 5−fold technique • N_h = 5 hidden layers • n_h = 128 neurons		properties • high robustness against measurement inaccuracies in the position and orientation of the UT
[50]	• Beam selection	Power Delay Profile •	Deep Neural Network	• ReLU activation function • mmWave carrier frequency = 28 GHZ • number of beams N = 16.64 • antenna element spacing 0.5 λ_0 • sub-6 GHz carrier frequency 3.5 GHz • UE grid spacing 0.5m • Transmit power 23 dBm • Thermal noise -100dBm	• *Overhead* • *accuracy*	• Reduce overhead • high beam selection accuracy • reduces the beam sweeping overhead up to 79.3%
[51]	• Beam selection	• Scalability • Robustness •	Deep Neural Network	• Dataset generated at 28 GHz band • test scenarios include three environments: a conference room (CR), a living room (LR), and an enterprise cubicle (EC), which are specified by the IEEE 802.11ad task group • ΔL, is set no more than 0:65m • Total number of training data and testing data are 120000, 180000, and 320000 samples	• *Overhead* • *accuracy*	• Beam selection without channel knowledge • Online beam selection overhead is reduced • At high Nbeam, TX, BsNet is more efficient • improve the image quality of BDRPM

From above survey table XI it is observed that beam selection using deep learning techniques helps in proper beam selection. It also results in reduction of beam misalignment and this improves system performance. Also, user terminal plays an important role in initial beam alignment procedure in pedestrian application.

4.4 Beam Alignment

TABLE XII Survey of Beam Alignment Technique Using Deep Learning

Paper	Parameter Predicted	Benchmark for Parameter Prediction	DL Model	Hyper Parameter	Performance Metrics	Salient Features of Developed Model
[52]	Blind beam alignment	• Data rate • System performance	Deep reinforcement learning	• Number of Hidden Layers, L = 2 • Hidden Nodes in layer [128; 128] • Buffer Size τ = 100000 • Discounting factor γ = 0:60 • λ = 0:001 • Actor learning rate, η_a = 0:0001 • Critic learning rate, η_c= 0:001 • Number of episodes 1000 • Steps per episode 1000	• Overhead • Sum rate	• Achieve a data rate of up to four times the traditional method without any overheads

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[53]	Accurate beam	Spectral efficiency	Recurrent network	• Time horizon: K = {0; 1;K-1} (frame duration) • *Dual timescale approach*	• Training Overhead • Gain • Signal to noise ratio	• spectral efficiency, with a gain of 85% that scans exhaustively over the dominant beam pairs • spectral efficiency, with a gain of 18% over a state-of-the-art POMDP policy • training overhead decreases and the spectral efficiency increases

From above table XII it is observed that beam alignment using deep learning technique helps in improving data rate and spectral efficiency of system.

4.5 Beamforming

TABLE XIII SURVEY OF BEAMFORMING USING DEEP LEARNING TECHNIQUES

Paper	Parameter Predicted	Benchmark for Parameter Prediction	DL Model	Hyper Parameter	Performance Metrics	Salient Features of Developed Model
[54]	• Channel State Information	• spectral efficiency • hardware limitation	Deep Learning	• N_t = 64 at BS • total number of FLOPs = 0.15 million • L = 3 (1 LoS, 2 NLoS paths) • Learning rate 0.001 • Adam optimizer	• Signal to Noise Ratio • System performance • gain	• robustness to imperfect CSI • improve performance spectral efficiency of 8 bits/s/ Hz achieves around a 1.5dB gain in SNR when PNR = 20dB
[55]	Posterial probability	Angle of Arrival	Deep Neural Network	• Number of antennae N = 128 • Minimum angle of arrival Φ_{min}= -60^0 • Maximum angle of arrival Φ_{max}=60^0 • M = 64 antennas at BS • number of uplink pilot transmission as τ = 2 $log_2(N)$ = 14 • TensorFlow and Keras • Adam optimizer • learning rate progressively decreasing from 10^{-3} to 10^{-5} • 10 batches per epoch	• Minimum Mean Square Error • Mean Square Error • Kalman filter estimation	• Initial access • better AoA acquisition performance
[56]	imperfect CSI conditions	• spectral efficiency • Throughput	Deep Neural Network	• Tenser flow & Keras package • BS antennas 64 • Operating frequency 28 GHz • ReLU activation function • Learning rate 0.001 • Adam optimizer	• Normalized Mean Square Error • Loss rate	• Improve spectral efficiency • Robust to imperfect CSI

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	• Samples for training & validation $8 * 10^3$ • 100 epochs • Batch size 64 • No. of channel paths L_{est}= 2 • SNR range -20 dB to 25 dB	

From above table XIII it is observed that loss rate depends on signal to noise ratio. As signal to noise ratio increases loss rate falls. The angle of arrival post arial distribution also improves with increase in signal to noise ratio.

V. CASE STUDY ON IMPLEMENTATION

A Framework for Beam Management in 5G Millimeter-wave Technology

5.1 Basic Theme of Study

One of the prime requirements in beam management is to accomplished high data rate. So, for the current wireless networks, this is one of the major challenges. Due to the shortage of spectrum in sub 6 GHz, one of the challenges is towards improving network performance. The solution to this is expanding the operating frequency to a higher frequency band i.e., millimeter wave frequency. MmWave band having wide bandwidth and high frequency ranging from 30 – 300 GHz can help in providing a high data rate. But still, it suffers from various propagation losses as compared to sub 6 GHz. To compensate for this, the utilization of the massive number of antennae is one of the ways with beamforming and beam management concerns [57]. The above has been the motivation towards addressing problem of beam management in mmWave networks.

5.2 Objective and Relevance of Work

5.2.1 Objective

The following is the main aim of the proposed system taken up in the case study.

To provide an effective solution to high path loss or penetration losses available at mmWave by introducing a comprehensive beam management system.

The above aim is being accomplished by the following objectives:

1. To reduce the high path loss in the channel state information using deep learning techniques.
2. To evaluate performance gain and reduction in overheads using beam training and beam tracking.
3. To improve the communication link between the base station and user using advanced deep learning-based beam selection methods.
4. To minimize power attenuation through directional beamforming based on deep learning.
5. To develop a comprehensive framework for beam management encompassing channel state information, beam training, beam tracking, beam selection and beamforming.

5.2.2 Relevance of Work

Channel estimation is used to get accurate channels by finding different parameters. Once the channel is formed tracking of a particular beam is necessary. In this angle of arrival and departure is calculated. After accurate angle formation, beams get selected to form a link at both ends. Then beamforming is done amongst the selected beams. After beamforming narrow beam is formed and effective communication is carried out between the mobile user and the base station. Overall, all the steps integrated in one frame is beam management which is carried out to improve system performance and to reduce path loss components.

5.3 Proposed Methodology

The proposed methodology will comprise of the following steps:

Beam management using deep learning is used to extract parameters from changing environments. As mmWave suffers from a high pathloss and reduction in path loss is necessary, high beamforming gain is required. To achieve high beamforming gain accurate beam alignment is needed as beam misalignment will results in loss in beam power. Deep learning is used to find beam direction for reducing beam training overhead. When a user is moving, to tracking the beam direction is necessary. To tackle this problem Deep Reinforcement Learning (DRL) is proposed for designing nonlinear variation in the line-of-sight condition. Due to the mobility of the user, blockages may be appeared or disappear according to the scenario. To tackle this problem beam management can be used to find changing environments and find new beam directions. Thus, beam management using deep learning is used to adapt to the changing environment.

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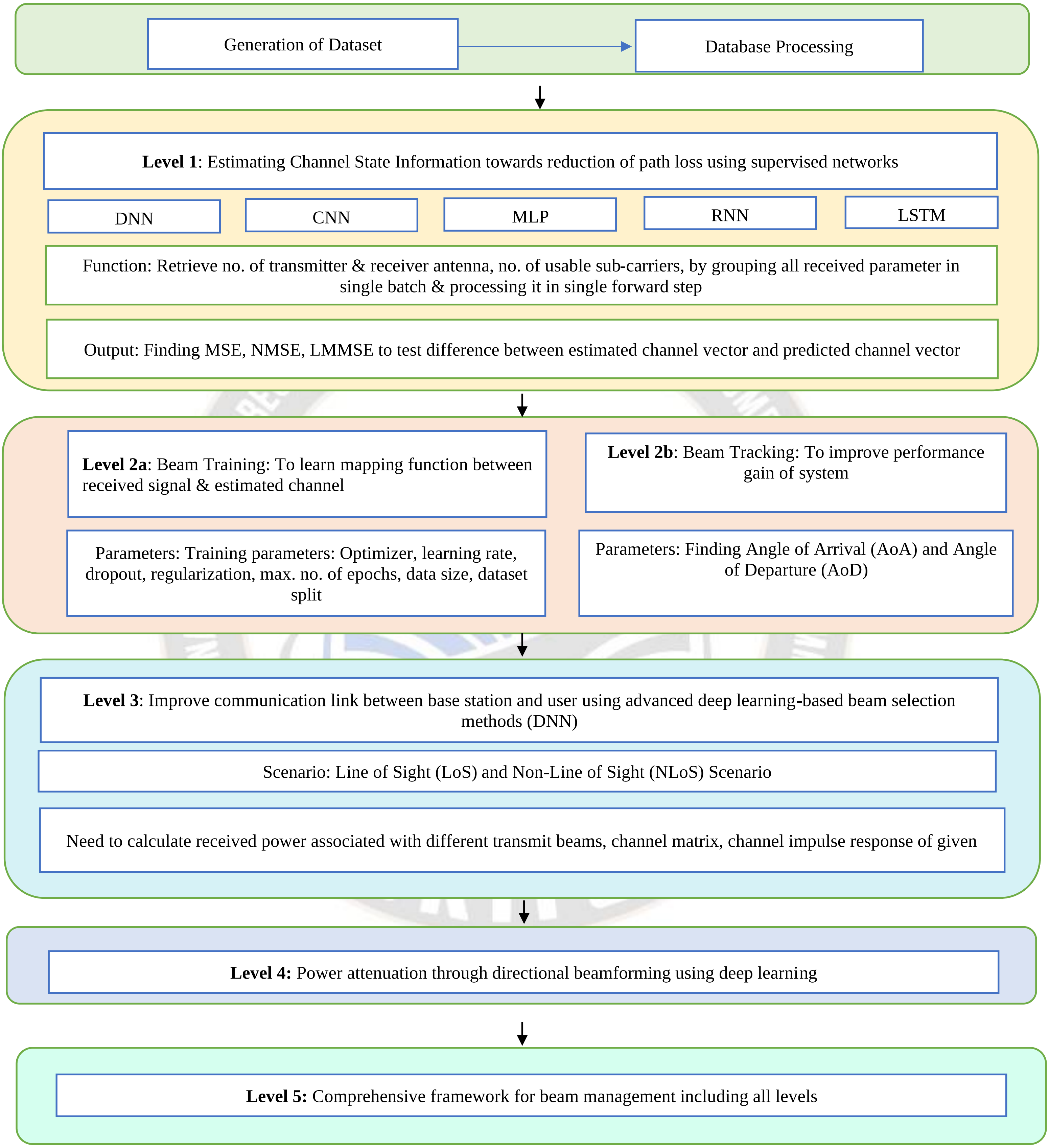

Fig. 5.3.1: Proposed methodology

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5.4 Expected Impact of Work

It is expected that the proposed beam management model will have impact on performance parameter which are being detailed below. Combining channel state information, beam training, beam selection, beam alignment, and beamforming in one comprehensive model i.e., beam management will be a major outcome of the proposed model. Further, making use of available datasets to build a system that provides a strong communication link between the user and the base station is one of the salient outcomes of the proposed work. The following are the other expected results out of the proposed methodology:

- A more accurate and efficient model as compared to the existing system will be accomplished.
- Obtaining a strong communication path at both ends.
- A strong communication link between the user and the base station will be achieved.
- Sufficient and accurate channel information will be available.
- Accurate beam tracking will be done.
- The best beam selection will be done.
- More devices can be connected at a time.
- A comprehensive solution for perfect beam management will be formulated.

5.5 Technical Novelty and Utilization

The combination of various technologies such as machine learning, neural network, artificial neural network, and predictive analysis through deep learning is a technical novelty in the proposed framework of beam management which is unexplored in literature. The techniques used in previous work are not very effective. The development of a robust system will be another technical uniqueness of the proposed methodology. In the proposed work, various steps are implemented using different technologies. Such a comprehensive solution will have high demand for the problem of various propagation losses available at mmWave frequency.

I. FUTURE RESEARCH DIRECTIONS

For a rapidly changing environment designing a beam management scheme is one of the challenging topics in the future. In each process in beam management there is huge scope for improvements. The following are some areas which can be explored further in beam management.

- Estimation of channel parameters in fast-moving scenarios.
- Design of beam alignment for scenarios like a strong wind.
- Design of Low Complexity technique for Beam prediction.
- Design of low-cost beamformer.

Further, one of the key directions of future research in beam management in millimeter wave communication is the development of advanced beamforming techniques. This includes the use of machine learning algorithms to optimize beamforming, the design of dynamic beamforming algorithms that can adapt to changing channel conditions in real-time, and the integration of beamforming with other wireless communication technologies such as massive MIMO. Another important research direction which has huge scope for work is the investigation of hybrid beamforming solutions that can effectively utilize both analog and digital beamforming techniques to improve the overall performance of millimeter wave systems. Additionally, research into new beam management schemes, such as beam tracking and beam switching, are likely play a crucial role in enabling the efficient use of millimeter wave spectrum for 5G and beyond.

Deep learning has shown promise in a number of areas in millimeter wave communication, including beam management. Some potential future research directions in this field include:

1. Development of deep reinforcement learning algorithms for beam management: Reinforcement learning algorithm can be used to optimize beam management by learning the best beam selection strategy based on feedback from the system.
2. Deep neural network-based beamforming optimization: Deep neural network can be trained to optimize the beamforming weights in millimeter wave system. This can result in improved beamforming performance compared to traditional methods.
3. Deep neural network for channel state information estimation: Channel state information in crucial for effective beam management. Deep learning algorithms can be used to estimate this information more accurately, leading to better beam management

Overall, the integration of deep learning with beam management in millimeter wave communication has the potential to significantly improve the performance and efficiency of these systems, making it a promising area for future research.

VI. CONCLUSION

This paper addressed challenges in millimeter-wave communication systems and studies the possibility of enhancing the coverage of mmWave using channel state information. The problem of large overhead is studied, which can be minimized using beam training technique and beam tracking technique improves performance gain of the system. The beam selection method is proposed to improve the communication link between transmitter and receiver. Power attenuation can be reduced by using directional beamforming. In this work the proposed methodology gives the path for performance improvement in beam management system in mmwave technology. This improvement can be accomplished by reducing path loss in the channel, reducing overheads using beam training, improving performance gain using beam tracking, establishing a strong communication path using beam selection, and performing power attenuation through directional beamforming. Such comprehensive beam management system in Millimeter wave technology will result in tremendous improvement in performance and hence finds wide range of applications in modern society for high speed, low latency communication. Some examples of applications are in medical imaging such as MRI, CT scans and non-invasive surgery as well as in airport security to detect potential threats without need for physical searches, in radar for collision avoidance and autonomous driving and in industrial sensing. Thus, the paper contributes comprehensive investigation of beam management using conventional and deep learning approach and will be a strong enabler in empowering millimeter wave technology in 5G.

VII. LIST OF ABBRIVIATION

TABLE XIV LIST OF ABBREVIATIONS

1G: First Generation	**2G:** Second Generation
4G: Fourth Generation	**5G:** Fifth Generation
mmWave: Millimeter Wave	**MIMO:** Multiple Input Multiple Output
LTE: Long-Term Evolution	**CS:** compressed sensing
CSI: Channel State Information	**UE:** User Equipment
LSTM: Long Short-Term Model	**DNN:** Deep Neural Network
NN: Neural Network	**ML:** Machine Learning
RNN: Recurrent Neural Network	**FDD:** Frequency Division Multiplexing
TDD: Time Division Duplex	**DL:** Deep Learning
IA: Interference-Aware	**BS:** Base Station
MS: Mobile Station	**UT:** User Terminal
gNB: next generation Node Bs	**NR:** New Radio
UE: User Equipment	**QoS:** Quality of Service
AoA: Angle of Arrival	**AoD:** Angle of Departure
AP: Access Point	**IA:** Initial Access
DQN: Deep Q network	**RF:** Radio Frequency
2D: Two-dimensional	**3D:** Three-dimensional
GPS: Global Positioning System	**GNSS:** Global navigation satellite system
UAV: Unmanned Aerial Vehicles	**DoF:** Degree of Freedom
IRS: Integrating large intelligent reflecting surfaces	

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