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Efficient Beam Selection in mmWave Cellular Systems Using Neural Networks and K-Nearest Neighbors Based on GPS Coordinates

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Abstract: With B5G moving towards 6G, the possibility of having even higher capacity and lower latency is becoming more realistic and expected to be driven more by mmWave frequencies. However, a major issue in these systems remains the downlink beam alignment and training procedure within mmWave cellular networks. Beam selection, as part of the physical layer and the medium access control sublayer, is critical for discovering and pairing superior beams for reliable connections. In this research, machine learning using neural networks (NN) and K-nearest neighbours (KNN) is proposed for selecting the beam based only on the GPS coordinates of the receiver. This method is more efficient than conventional methods that may involve, for instance, protracted or computationally expensive beam searches or hard-to-obtain side information. An improved selection is achieved by proposing a novel selection architecture in the proposed method using NN-KNN while ensuring the best performance out of competing methods by using the average received signal reference power (RSRP) and top-K accuracy metric. This approach has shown that, despite imprecise data of the receiver location, it is a more efficient solution for future wireless communications systems. The results imply potential improvements in beam selection concerning efficiency, which can support the further development of mmWave for future B5G and 6G networks.

Keywords: Beam Selection, Neural Networks, K-Nearest Neighbors, Beam management, Wireless Communications

1 Introduction

As for the B5G and 6G wireless systems, they show an apparent trend towards a substantially higher capacity and lower latency compared to the current LTE systems [1], [2] and [3]. There is the possibility of transforming this situation due to the ability to use millimeter-wave (mmWave) frequencies ranging approximately from 30-300 GHz, whereby the available bandwidth is extremely large. However, a technical challenge arose in downlink beam alignment/training in the domain of mmWave cellular systems.

Beam management, which surrounds a range of Layer 1 and MAC layer procedures, is carefully combined to define and maintain a proper beam pair. This makes the transmit beam and its associated receive beam this crucial pair for establishing stable and reliable links. It will be important to recognize that the source of this process is related to the determination of the BF direction to the Subscriber Device (SD), which is a central stage in creating what is called the Primary Connection (PC). PC is defined as a procedure through which an SD makes a mechanical and logical connection with a Gateway as an initial step to data transmission [4]. Unlike the conventional cellular systems, in which the sounding signals are released into all directions, followed by establishing the physical link connection of BF, the mmWave communiqué requires the incorporation of the BF into the initiation stage of the PC phase. This tactical modification is compulsory for harnessing the vast

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directionality advantage provided by the muteness of mmWave antenna arrays, which is a very useful ability necessary for circumventing the serious challenges of high path loss in alternate mmWave mobile networks. They are equally significant in Beyond 5G and 6G wireless systems where fine-tuning beam management procedures is indispensable for enhancing the set's value that harnesses these systems [5].

In the presented scenario, the future development of millimeter-wave (mmWave) technology entails marked growth in the number of antenna elements used in the corresponding communication systems. This expansion is expected to increase with the usage of higher frequencies in future revisions. In the case of the PC phase within the 5G New Radio (NR) framework, the compared phase is beam sweeping, which implies rather extensive searches on the exhaustive set of beams both at the transmitter and the receiver ends. This thorough search is meant to find the beam pair of the highest reference signal received power (RSRP). This holds because, with the new era of mmWave communications, there is an increase in the number of antenna elements and beams, making the computational cost of exhaustive beam searches rocket. Thus, these extensive searches result in long initial access times, which can be a major problem for network operations [6].

A hierarchical search methodology has been presented in[7], to meet this challenge. In this approach, the Gateway undertakes a serial, top-down exploration over broader beams before tightening to the narrower ones in subsequent steps. Although this search strategy reduces latency compared to exhaustive searches, it unintentionally lowered the MUEs' coverage at the cell's edge. This restriction has also been observed in[8], showing that different BM decision approaches for network performance maximization come with trade-offs. It was found that recent investigations have introduced context information (CI) to support approaches to beam training. The Gateway in [9] and [10] tilts its beam towards the nearest SD, relying on the geographical position of the SDs. However, these strategies may be disrupted and cause inaccuracies arising from barriers between the nearest Gateway and SD. Instead, [?] describes a method in which the Gateway uses a prior multipath fingerprint measurement repository. The suggestion has been made in [?] and [13] to use out-of-band information below 6 GHz for beam alignment at mm-wave frequencies. In the same context, [14] proposes a beam alignment scheme for vehicle communication that relies on onboard radars.

Several studies have explored integrating Machine Learning (ML) techniques into the beam training process. Typically framed as a classification task, machine learning algorithms leverage extrinsic information such as lidar data, GPS signals, and roadside camera images to recommend a subset of promising beam pairs. This approach mitigates the need for exhaustive searches by focusing the beam selection process on the selected subset. For instance, [15] utilizes received omnidirectional sounding signals from multiple gateways to predict the optimal beam. Nevertheless, this method is vulnerable to mismatches between the coverage ranges of sounding signals and beamforming communication. In contrast, [16] formulates the beam training problem within a multi-armed bandit framework, while [17] trains ML models to predict optimal beams in vehicular networks using the locations of all vehicles.

This research introduces a novel approach that harnesses the power of neural networks (NN) and K-nearest neighbours (KNN) for beam selection, utilizing solely the GPS coordinates of the receiver. The proposed technique requires only the locations of SD. The SD can easily acquire these locations by leveraging technologies such as GPS and developing localization algorithms. Moreover, the transmission of DS locations can be conveniently accomplished over lower-frequency lines, a feature already endorsed in LTE's Minimization of Drive Tests (MDT) mode and expected to undergo additional standardization in the coming years. The method being proposed exhibits robustness in the face of inaccuracies in DS locations, in contrast to prior methodologies that depend on more difficult-to-acquire supplementary data, such as radar measurements [18], received sounding signals from multiple gateways [19], and multipath fingerprints [20]. By fixing the transmitter and scattered locations, the research generates training samples comprising receiver locations (GPS data) paired with the true optimal beam pair index, determined through exhaustive search. A novel NN-KNN architecture is designed and trained using this dataset, where the receiver's location serves as input and the true optimal beam pair index as the label. During testing, the NN-KNN model outputs a set of K promising beam pairs, followed by an exhaustive search over these candidates to select the final beam pair with the highest average RSRP. The proposed method is evaluated using two key metrics: average RSRP and top-K accuracy. The methodology's effectiveness is assessed based on its ability to streamline the beam selection process while maintaining high-performance metrics. The subsequent sections of this paper delve into the method, experimental results, and implications of the proposed approach for enhancing beam selection efficiency in wireless communication systems.

2 Background

Beamforming is a technique that enhances wireless communication and sensing systems by the intelligent concentration of signals toward specific targets. The manipulation of weights and phases of signals generated by individual antenna elements allows for the direct control of the primary lobe of the antenna's emission pattern. This technology enhances the quality of signals, increases the system's capacity, and optimizes resource utilization, rendering it indispensable for contemporary and forthcoming communication systems. There are two distinct categories of beamforming techniques. Phase shifters and attenuators are employed in the process of analogue beamforming. This approach is straightforward and appropriate for systems with limited antennas. Digital Signal Processing (DSP) uses digital beamforming to modify signals after converting from analogue to digital. This technology facilitates the utilization of sophisticated and adaptable beamforming algorithms, rendering it well-suited for extended antenna arrays. The early development of three beamforming methods encompassed the time-domain, frequency-domain, and hybrid approaches. Time-domain beamforming is a technique that utilizes signal time-delays to achieve constructive alignment. The system employs a delay mechanism for received signals to achieve constructive summation in the desired direction. Frequency domain analysis is widely used in several domains. Beamforming involves the blending of signals from several antennas in terms of frequency. The primary lobe can be oriented by adjusting the signal weights [21].

Hybrid beamforming achieves a harmonious equilibrium between system complexity and performance by integrating analogue and digital beamforming techniques. The suggested approach eradicates radio chains and analogue components while retaining some advantages of digital beamforming. Beamforming encounters two significant challenges. Digital beamforming can be computationally demanding when handling several antennas and data streams. Optimal results in beamforming necessitate accurate channel state information. Acquiring accurate CSI is challenging, particularly in dynamic settings. The acronym BS denotes multi-beam systems capable of generating beams in many directions [22].

The system employs a dynamic methodology to choose the most optimal beam from a predetermined set to establish communication with a user or device. This selection is contingent upon the specific conditions of the channel and various other considerations. Beam selection is an automated process that aims to optimize communication performance and resource usage by selecting the most suitable beam for each user. Due to their excellent directionality, multiple antennas in large MIMO and mmWave systems necessitate meticulous beam selection for each user. Beamforming is crucial for the selection of beams. Before beam selection, the system is required to generate several beams through beamforming. Beamforming generates test beams to select a beam. Beam selection involves the utilization of beamforming weights and CSI data to assess potential beams suitable for a user's specific channel conditions. Beam selection is a technique that enhances communication and improves the performance of beamforming systems by dynamically selecting the most suitable beam for each user. The beamforming process involves the generation of many beams, whereas beam selection utilizes real-time channel circumstances to determine the optimal beam for individual users autonomously. The integration of these elements enables the effective and adaptable utilization of antenna resources, rendering it indispensable for contemporary wireless communication systems, particularly in scenarios involving extensive antenna arrays and fluctuating channel conditions [23].

2.1 Beam selection methods

Modern wireless communication systems, especially those with many antennas, require beamforming. The above methodologies use dynamic selection to get the best beam from a set of beams to optimize communication with a user. We will discuss beam selection methods in this discussion:

The maximum ratio combining: the receiver combines the signals from many antennas to maximize the signal strength. MRC is applied to MIMO systems to enhance communication capacity and reliability. Conventional MRC is beneficial in multipath fading scenarios such as reflections, diffractions, and scattering [24].

The transmit beamforming enhances the quality of the signal and lowers the interference since the signal transmitted steers in a certain direction. Transmit beamforming is one method used in directional antennas to enhance data rate. This is true when the spectrum resources are scarce, and the bandwidth is narrow; in this case, transmit beamforming is beneficial and needs to be optimized [25].

Receive beamforming: increases the signal quality and reduces interferences because the received signal appears to come from a particular direction. Receive beamforming is widely applied in MIMO systems to improve communication flexibility and dependability. Receive beamforming is very useful when there is much interference, hence endangering the signal. This is more likely when the signal is exposed to noise and other forms of interference [26].

Codebook-based beamforming: This method uses a pre-existing codebook to select the optimal beam direction. Codebook-based beamforming is simple and efficient, making it popular in natural systems. Codebook-based beamforming reduces beam selection complexity in cases with limited processing resources [27].

Machine learning-based beam selection, such as neural networks, in beam selection can help identify the optimal beam direction by exploiting the CSI. Machine learning algorithms for beam selection can improve network performance by responding to dynamic channel circumstances. Machine learning techniques for beam selection are beneficial in complex and ever-changing channel conditions, where the best beam direction may vary over time. Machine ML improves beam selection in future wireless communications. Table 1 shows that this approach achieves flexibility, optimization, and increased performance in complex and dynamic circumstances. Machine learning algorithms must be carefully designed and trained to provide reliable and durable performance in practical scenarios [28].

Modern technologies like AI, ML, and DL have changed many parts of our existence. These technologies affect wireless communications, communication security[29], finance, healthcare, driverless vehicles, natural language processing, and many other fields.

AI allows computers to think and learn like humans. AI aims to enable computers to do human-like activities like visual perception, speech recognition, decision-making, and language comprehension. Machine learning and deep learning are used in AI to make machines smart.

ML is a branch of AI that develops algorithms and statistical models to help computers learn and improve from data without being programmed. ML algorithms learn patterns, predict, and act on data. Machine learning includes supervised, unsupervised, and reinforcement learning [30]. ML has a specialized subfield called DL. For complex problems, it uses artificial neural networks as computer models. The brain's physical and metabolic properties inspired DL algorithms with numerous layers of interconnected artificial neurons. In picture analysis, language understanding, and speech interpretation, neural networks perform well because they can learn autonomously and encode data across multiple levels of abstraction. Artificial intelligence applications have advanced significantly thanks to DL.

ML models that mimic the brain's anatomy and function are called NN. ML algorithms are used for Classification, regression, image recognition, NLP, and other tasks. NN are layers of interconnected artificial neurons that process and learn data patterns. NNs do forward and backpropagation iteratively. Forward propagation sends input data through a neural network's layers. An activation function is applied after computing a weighted total of inputs at each neuron. An activation function adds non-linear properties to the model, making it easier to learn complex dataset relationships. After forward propagation, the model's predictions are compared to labels. A loss function is used to measure prediction error. Backpropagation calculates loss function gradients relative to model parameters. Gradients are used to optimize model parameters using stochastic gradient descent (SGD) or Adam. The above approach iterates over numerous epochs until the model converges and yields a good solution [31].

The KNN algorithm is a simple ML approach used for Classification and regression. The KNN method assumes that data instances with similar features are more likely to be grouped or have similar target values. The main procedure uses a dataset with class labels or goal values. The goal is to find the best value for 'k,' the number of nearest neighbours to consider while predicting new data points. During prediction, the KNN algorithm estimates the distance between the latest data point and all other training set data points. This is usually done with Euclidean or Manhattan distance. KNN algorithm finds the 'k' nearest data points to find the class label with the highest frequency in Classification or the regression task's average target value for the new data point. The selection of 'k' strongly affects KNN algorithm performance. Intricate decision boundaries with noise can be created with a smaller 'k.' A higher 'k' creates smoother decision limits. Fe scaling is essential to ensure that all features contribute proportionally to distance calculation. KNN is also a non-parametric method because it makes no data distribution assumptions. It learns from training data directly. KNN is easy to implement, but it requires calculating distances to all training points for each prediction, which increases processing costs for larger datasets [32].

3 Methodology

The beam selection algorithm integrates the predictive capabilities of NN with the localized reasoning of KNN to achieve a resilient and precise selection of ideal beam pairings for wireless communication across diverse settings. Integrating these algorithms seeks to optimize the overall efficiency and flexibility of the beam selection procedure. The primary objective of the beam selection algorithm is to identify the most favourable combination of transmit and receive beams in a wireless communication system to maximize the received signal power, also known as the received signal reference power (RSRP). The selection of optimal beams is determined by evaluating the projected performance of a collection of candidate beams. This approach comprises two primary constituents: the NN and the KNN classifier.

3.1 System Model

Consider a scenario with a transmitter and receiver pair, each equipped with analogue antenna arrays comprising Nt and Nr antenna elements. Additionally, let's assume there are fixed and pre-established DFT codebooks at both ends, denoted by

$$H = \{h_1, \ldots, h_{|H|} : h_i \in \mathbb{C}^{N_t \times 1}\}, \tag{1}$$

for the transmitter and

$$D = \{d_1, \ldots, d_{|D|} : d_i \in \mathbb{C}^{N_r \times 1}\} \tag{2}$$

for the receiver. In this context, for a given channel $H \in \mathbb{C}^{N_r \times N_t}$, which is usually estimated or unknown at both ends; the beam selection problem entails maximizing the beamformed channel gain by selecting the pair of transmitter and receiver beams, expressed as:

$$\max_{(i,j)\in|H|\times|D|} g(i,j) = \left|d_j^T H h_i\right| \tag{3}$$

Table 1: Table 1 compares the traditional and machine learning techniques used in the beam selection process.

Criteria	Machine Learning-Based Beam Selection	Traditional Beam Selection Techniques
Basis	The methodology employed in this method is characterized by a data-driven approach, which involves the utilization of real-world data and experiences for learning and analysis.	The utilization of predetermined tactics and heuristics in rule-based approaches.
Adaptability	The system exhibits high adaptability when faced with changing channel conditions and user mobility.	The system's adaptability is constrained and heavily dependent on predetermined codebooks or rule-based mechanisms.
Complexity	The adoption of this approach necessitates a more intricate process involving the acquisition of data and subsequent training.	A more streamlined implementation with reduced computational overhead.
Performance	The proposed approach performs better than conventional approaches, particularly in intricate situations.	The system's suitability is sufficient for basic applications, although it may exhibit suboptimal performance in specific scenarios.
Optimization	One can optimize the selection of beams to achieve specific aims.	The optimization capabilities are limited.
Beam Codebook	Can generate optimized beam codebooks tailored to environments	Relies on fixed, predefined codebooks.
Interference Mitigation	The ability to effectively reduce interference is enhanced by using acquired patterns.	A set of straightforward measures constrains the ability to manage interference.
Training Data	To achieve optimal performance, the utilization of training data is necessary, and it is imperative to update the model regularly.	Utilizing training data is unnecessary as the decision-making process is based on predetermined rules.
Real-time Decision	The ability to make real-time judgments is enhanced following a period of training.	Real-time decision-making processes that rely on pre-established rules.
Suitability	This technology is highly suitable for intricate situations characterized by expansive antenna arrays.	Appropriate for elementary systems characterized by a limited number of antenna combinations.

This involves selecting the transmitter and receiver beam pair that maximizes the beamformed channel gain.

However, due to the imperfect knowledge of the quantity to maximize (precisely estimating H is often unfeasible, especially in the massive MIMO regime), the beam selection problem is typically addressed through sequential procedures[33]. Moreover, it is frequently likened to a multi-armed bandit problem [34].

3.2 Data Collection and Preprocessing

– The method begins by acquiring training and test data from a pre-established scenario. The training dataset comprises the geographical coordinates of receivers, and for each receiver location, the method computes the channel's received signal strength indicator (RSSI) for every potential beam pair [35].
– Using a ray-tracing propagation model generates the dataset utilized to train the model in practical applications. The utilization of the ray-tracing model is prevalent in the realm of wireless communication research as a means to forecast the behaviour of radio wave propagation within intricate settings. The software programmer emulates electromagnetic wave transmission by tracking individual rays' trajectories as they undergo reflection, refraction, and diffraction while interacting with objects and surfaces within their surroundings. The procedure for constructing the real-world dataset can be succinctly outlined as follows:

a) **Environment Modelling:** The process of environment modelling involves the creation of a representation of the physical surroundings, encompassing various elements such as buildings, walls, obstacles, and other structures that have the potential to influence the propagation of radio waves. The propagation model is a 3D Geometric-based mmWave channel model [36].

b) **Antenna Placement:** The simulation represents every element present in the environment. The precise positions of the transmitter and reception antennas are designated within the given environment. Multiple elements (arrays) can be incorporated into these antennas to facilitate beamforming. An 8x8 Uniform Linear Array (ULA) is used in the transmitter to provide 16 beam pair.

c) **Ray Tracing:** The ray-tracing algorithm initiates the emission of rays from the transmitter antenna and subsequently monitors their trajectories as they engage with the surrounding environment. Rays can undergo reflection off walls, bounce off surfaces, and exhibit diffraction phenomena [37].

d) **Channel State Information (CSI) Collection:** The algorithm acquires CSI for every ray during the ray-tracing procedure. CSI encompasses data about the received signal's magnitude and phase for each ray at the reception antenna. This data describes the behaviour of the channel, including attributes such as signal strength and phase shifts [38].

e)**Optimal Beam Pair Generation:** An ideal beam pair is determined for each simulated channel realization, which includes CSI. The beam pair presented above exemplifies the optimal amalgamation of transmit and receive beams, maximizing the power of the received signal or minimizing interference.

f)The data undergoes preprocessing to facilitate the training of the neural network and the application of the KNN technique [39]. The data is split into two parts. The first is 80% of the whole dataset for the training phase. The second is 20% of the entire dataset to test the algorithm.

3.3 Neural Network Training

–The training of the NN involves utilizing the training data, wherein the input to the network consists of the coordinates of the receiver position, and the output corresponds to the predicted optimal beam pair index, as shown in Fig. 1.

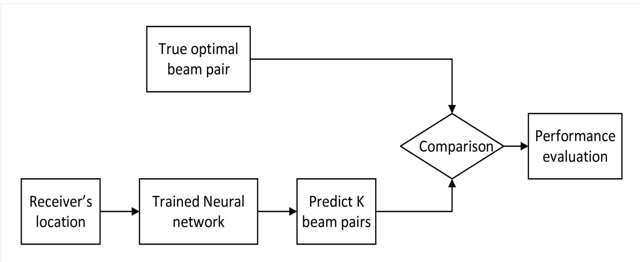

Fig. 1: Training Phase.

–During training, the NN acquires the ability to comprehend and represent the intricate connections between receiver locations and their corresponding ideal beam pair indices. This acquired knowledge enables the network to make accurate predictions regarding the optimal beam pair for receiver sites it has not encountered before. The input layer has two neurons, one for the receiver's x-coordinate and one for the receiver's y-coordinate. The output layer has 16 neurons, one for each possible beam pair. The network uses three hidden layers, each with 100 neurons. The hidden layers use the ReLU activation function. The ReLU activation function is a non-linear function that is practical for neural networks.

–During the training phase, the neural network is trained using the stochastic gradient descent (SGD) algorithm. The stochastic gradient descent (SGD) technique is an iterative optimization method that adjusts the weights of a neural network by considering the prediction errors. The Adam optimizer was utilized for stochastic gradient descent (SGD). The Adam optimizer is a hybrid optimization algorithm that incorporates the benefits of both the AdaGrad and RMSProp optimizers. The AdaGrad optimizer employs a learning rate inversely proportional to the square root of the cumulative sum of the squared gradients. This implies that the learning rate is higher for weights that have undergone minimal updates and lower for weights that have experienced significant updates. The RMSProp optimizer employs a learning rate that is inversely correlated with the root mean square of the gradients. This implies that the learning rate is higher for weights with significant gradients and lower for weights with minimal gradients. The Adam optimizer integrates both approaches by employing a learning rate inversely proportional to the square root of the cumulative sum of the squared gradients. This cumulative sum is further averaged across a specified number of previous steps. This approach aids in mitigating the issue of the learning rate becoming excessively little or excessively large. The Adam optimizer is widely favoured for training neural networks due to its ease of implementation and demonstrated efficacy across several tasks. The evaluation of the procedure is performed using the cross-entropy loss function. The cross-entropy loss function is a commonly employed loss function for assessing the efficacy of neural networks. The cross-entropy loss function quantifies the disparity between the expected and goal probabilities. The cross-entropy loss function quantifies the accuracy of a neural network in predicting the appropriate class for individual input points. A neural network performs better when the cross-entropy loss is more minor. The cross-entropy loss function can be formally stated as follows:

$$H(y,p) = -\sum_i y_i \log(p_i) \tag{4}$$

Where:y_i is the target vector, which is a one-hot vector that indicates the correct class for each data point. p_i is the predicted probability vector, which is a vector of probabilities that the neural network assigns to each class for each data point.

3.4 KNN Approach

–Once the neural network has undergone training, the method utilizes the KNN strategy on the test data to enhance the beam selection process.

–The algorithm finds the KNN from the training data for each receiver location in the test data based on the Euclidean distance metric (distance between receiver locations).
–The KNN technique generates k candidate beam pairs by leveraging the beam pairs linked to the KNN.

3.5 Combined Beam Selection

–The algorithm acquires two sets of candidate beam pairs for each receiver position in the test data:
  –Candidate beam pairs predicted by the NN (Top-K predictions).
  –The candidate beam pairs derived using the KNN technique.
–The algorithm merges the two sets of possible beam pairs by performing a union operation on the sets. The current collection comprises beam pairs that have been predicted by either the NN or picked by the KNN algorithm.

3.6 Final Beam Selection

–The algorithm chooses the most suitable beam pair from the collective set of potential beam pairs for every receiver position. The selection process is predicated upon evaluating each beam pair's received signal strength (RSS), with the algorithm opting for the beam pair exhibiting the highest RSS.
–The beam pair that is ultimately chosen is the one that the algorithm uses to transmit data to the receiver.

3.7 Evaluation Metrics

During the testing phase, the system operates with unseen data, which comprises the remaining portion of the dataset that was not utilized during the training phase. The testing process commences by inputting the location of the Subscriber Device (SD), which serves as the starting point for beam selection. The system predicts the K most suitable beam pairs for the given SD location by leveraging the trained Neural Network (NN) and K-Nearest Neighbors (KNN) algorithms. Subsequently, the predicted beam pairs are juxtaposed against the true optimal beam pair associated with the SD location. This comparison is facilitated through the utilization of performance evaluation metrics, which provide quantitative insights into the effectiveness and accuracy of the beam selection process, as shown in Fig.2

Performance Evaluation Metrics serve as crucial benchmarks for assessing the quality of predictions made by the NN and KNN algorithms. These metrics encompass various parameters, including but not limited to precision, Recall, accuracy, and top-K accuracy. By analyzing these metrics, the system can discern how closely the predicted beam pairs align with the optimal beam pair for the given SD location.

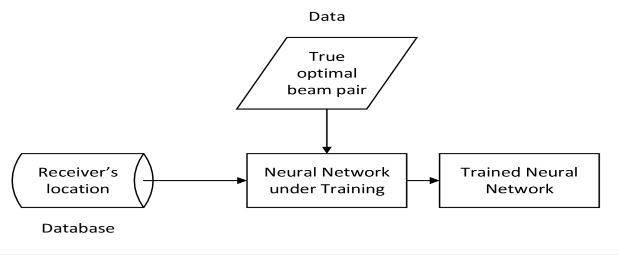

Fig. 2: Testing Phase.

In the context of the classification problem, consider $Y = \{1,\ldots,m\}$ as the output space representing all possible gateways or beams. The true optimal gateway or beam for an SD with coordinates x is represented by $y \in Y$. The vector $p \in [0,1]^m$ denotes the posterior probabilities predicted by the Machine Learning (ML) model, where each element p_i corresponds to the probability of y being equal to i given x.

$$p_i = P(y = i \mid x) \tag{5}$$

The k-th most significant element in p is denoted as $p_{\bar{k}}$. Let β denote a function that maps p to a set of candidate gateways or beams to search.

The proposed beam training method utilizing ML models is assessed using three metrics:

1. Accuracy is the likelihood of accurately predicting the sole optimal gateway or beam. Formally,

$$\beta(p) = \arg\max_{i\in Y}(p_i) \tag{6}$$

and the loss is given by

$$L(p,y) = \mathbf{1}_{(\beta(p)\neq y)} = \mathbf{1}_{\left(\max_{i\in Y} p_i > p_y\right)} \tag{7}$$

2. Precision and Recall for a given class represent the proportions of correctly predicted samples among all samples predicted to belong to that class and among all samples that genuinely belong to that class. Mathematically, precision is calculated by:

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \tag{8}$$

while Recall is computed as:

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \tag{9}$$

Since gateway and beam predictions involve multiclass problems, the models are assessed based on average precision and recall across all test samples.

3. Top-k accuracy measures the likelihood of correctly identifying the optimal gateway or beam among the top k gateways or beams. Mathematically, $\beta(p)$ is given by:

$$\beta(p) = \{i \in Y \mid p_i \geq p_{(\bar{k})}\} \tag{10}$$

The loss function is defined as:

$$L(p,y) = \mathbb{1}_{y \notin \beta(p)} = \mathbb{1}_{p_{\bar{k}} > p_y} \tag{11}$$

It's worth noting that accuracy is synonymous with top-1 accuracy, indicating the probability of correctly predicting the optimal Gateway or beam when considering only the top-ranked prediction.

4 Results and Discussion

The dataset preparation process is initiated based on the system described in the reference. The present dataset has been curated to facilitate the application of supervised ML techniques. The system was comprised of a total of 16 pairs of beams. The transmitter, known as the network node, experienced interference from twenty objects in various positions. On the other hand, the receiver, referred to as the user equipment, was placed in two hundred randomly selected locations, as depicted in Fig. 3. The given activity area is a square of 6m by 6m. The dataset was generated based on the receiver's position and the optimal beam pair that maximizes the RSRP.

Fig. 4 illustrates the likely depiction of the precision of the beam selection techniques about the varying number of beam pairs denoted as K. Precision is a metric that evaluates the correctness of positive predictions, specifically the accurately predicted beam pairings, concerning all positive predictions. The assessment of the models' proficiency in generating precise positive predictions is facilitated by varying the value of K.

Fig.5 illustrates the relationship between the model's Recall and the varying values of K. The metric of Recall, which is alternatively referred to as sensitivity or true positive rate, quantifies the proportion of accurate positive predictions concerning the total number of real positive instances. Evaluating the model's ability to forecast positive cases accurately is crucial when considering the variation in the number of anticipated beam pairs.
Approach Comparison: Top-K Accuracy

In this phase, the top-K accuracy metric is employed to assess the performance of the hybrid algorithm on unseen test data. This metric is a standard measure utilized in neural network-based beam selection methodologies.

The hybrid NN and K-NN algorithm jointly generate K-recommended beam pairings based on a receiver position. These recommendations undergo an exhaustive search, with the beam pair chosen as the highest average Received Signal Strength Indicator. A successful prediction occurs if the final selected beam pair matches the genuine optimal pair, the neural network, or the KNN algorithm recommends the genuine optimal pair. The algorithm finds two possible beam pairs for each receiver

position in the test data: The neural network predicts Top-K beam pairs in the first batch. KNN-derived candidate beam pairs are in the second set. A union operation merges these two sets of probable beam pairings, resulting in a collection of beam pairs predicted by the neural network or picked by the KNN method. To provide a benchmark, NN and KNN algorithms are considered, each generating K-recommended beam pairs:

NN Given a receiver location, the neural network first outputs K recommended beam pairs. Then, it performs an exhaustive sequential search on these K beam pairs and selects the one with the highest average RSRP as the final

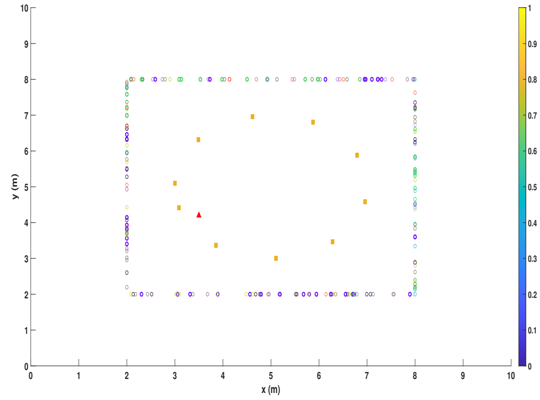

Fig. 3: Transmitter, Clutters, and receiver locations with optimal beam pair indices.

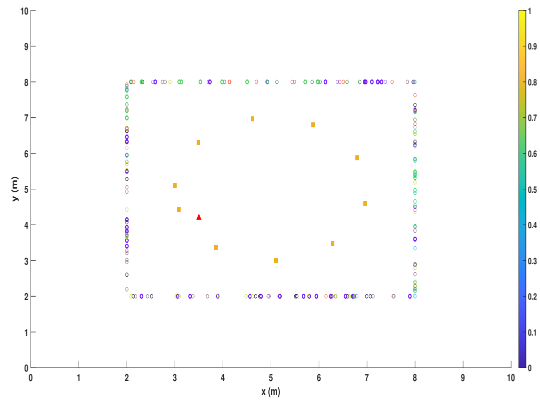

Fig. 4: Precision value comparison of different beam pair selection schemes with a changed number of beam pairs.

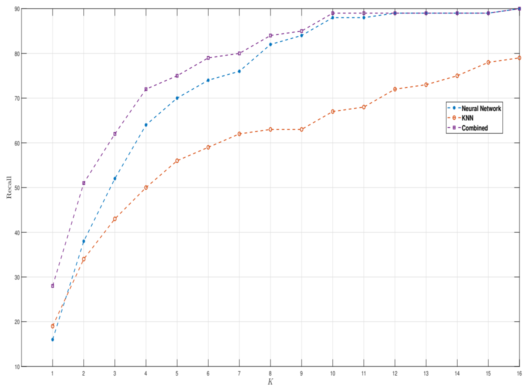

Fig. 5: : Performance Comparison of Beam Pair Selection Schemes with Variable Number of Beams: Recall Analysis.

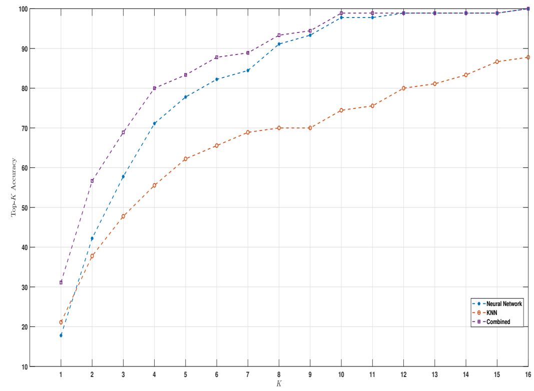

Fig. 6: Performance Comparison of Beam Pair Selection Schemes with Variable Number of Beams: Top K Accuracy Analysis.

prediction. A successful prediction occurs if the true optimal beam pair is the final beam chosen pair. Equivalently, success happens when the true optimal beam pair is one of the K-recommended beam pairs by the neural network.

KNN with GPS Coordinates: This method selects the K nearest training samples for a test sample based on GPS coordinates, proposing all beam pairs from these K training examples. While the maximum number of recommended beam pairings is K, some may be repeated.

The analysis reveals that the trained neural network selects beam pairs with K set to 8. For each technique (excluding KNN), exhaustive searches across all 16 beam pairings lead to 100% accuracy when K equals 16. However, KNN's performance is notable; although it chooses the 16 closest training samples when K is 16, the number of distinct beam pairings generally falls short of 16. Consequently, KNN fails to achieve 100% accuracy under these conditions as in Fig. 6.

Fig. 7 likely illustrates the F1-score of the beam selection algorithms about various values of K. The F1-score is a statistic that quantifies the balance between precision and Recall by calculating their harmonic mean. It serves to address the trade-off between these two performance measures. The provided analysis comprehensively evaluates the model's efficacy across varying quantities of predicted beam pairs.

Fig. 8 illustrates the mean Reference Signal Received Power (RSRP) about the variable K. RSRP quantifies the magnitude of the received signal. This observation demonstrates the impact of the selection of K on the quality of the received signal. The evaluation of the chosen beam pairings is facilitated by analyzing the signal strength they offer, which aids in determining their quality.

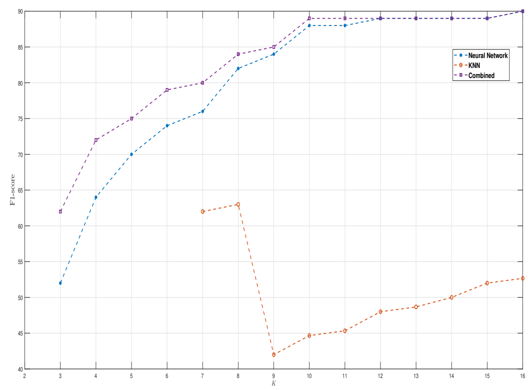

Fig. 7: Performance Comparison of Beam Pair Selection Schemes with Variable Number of Beams: F1-score Analysis.

Figures 3 through 8 are pivotal in analyzing the performance of the beam selection system across diverse settings and understanding its impact on the system's accuracy, precision, Recall, F1-score, and signal quality. These findings significantly contribute to comprehending the effectiveness of various beam selection algorithms in wireless communication environments. The hybrid suggestion algorithm, which combines KNN and NN algorithms, demonstrates superior performance compared to using NN or KNN algorithms independently, mainly when dealing with a limited number of beam pairs. Decreasing the number of beam pairings could potentially simplify the system, reducing complexity in both beamforming and signal processing operations. Reducing

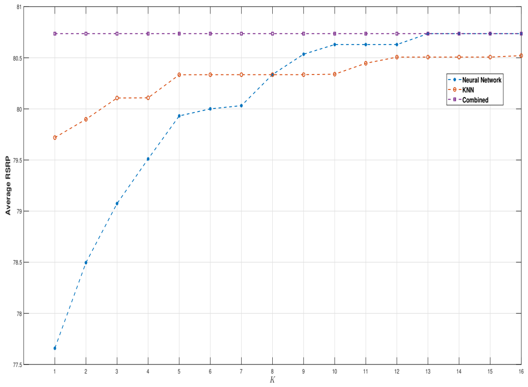

Fig. 8: Performance Comparison of Beam Pair Selection Schemes with Variable Number of Beams: Average RSRP Analysis.

the number of beams also lowers the probability of interference between adjacent beams.

5 Conclusion

In this paper, a new method for beam selection in mmWave cellular systems was proposed, employing the GPS position of the receiver as an input to a neural network (NN) and K-nearest neighbours (KNN) algorithm. This method solves the existing problems of traditional beam management methods, which involve the need to perform multiple beam searches and provide extra complex input data. This enables the NN-KNN architecture to reduce the number of beams, thus simplifying beam selection without compromising performance, as witnessed by factors such as average RSRP and top-K accuracy. The simulations reveal that our procedure is immune to receiver location estimate errors, which indicates that it can be used effectively in future wireless communications systems.

Therefore, by enhancing the complexity of beam selection, this method enhances the applicability of the mmWave technology in B5G and 6G networks. The efficiency gain in beam management improves connectivity and supports the achievement of the high capacity and low latency expected in the next-generation wireless networks. Further model development will involve fine-tuning its parameters, identifying new features that can be incorporated, and applying the method to various real-world problems to assess its practical applicability. This study contributes to achieving enhanced beam control in state-of-the-art wireless communication systems.

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