Two Stages Beam Selection Method Using Machine Learning and Peak Finding Algorithm

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***Abstract*—** The Multiple-Input and Multiple-Output (MIMO) techniques have been evolved significantly in recent decades. We expect to reshape the 6G cellular networks by adopting new innovative techniques. In particular, beamforming is used to allow for directional multiple beams by weighting magnitude or phase of signals in multiple antennas. It can improve spectral efficiency, reduce interferences, and expand coverage. It will be helpful for maintaining faster and more reliable connectivity in 6G networks. However, there are still many research challenges to design and implement beamforming systems. We need to optimize beam management schemes in terms of beam selection, connection set-up time, energy efficiency, throughput, network outage, QoS/QoE, and so on. It is not easy to find optimal network parameters and keep good link quality. The 3rd Generation Partnership Project (3GPP) 5G New Radio (NR) beam selection is based on exhaustive search method, Grid-of-Beams (GoB) and precoding matrix indicator (PMI). The exhaustive search method results in a long beam search time, a high overhead cost, and a high energy consumption. In this paper, we propose two stages beam selection method consisting of machine learning and peak finding algorithm to reduce beam sweeping overhead by predicting the beam selection subset and finding the optimal beam pair efficiently.

***Index Terms*—MIMO, 5G, 6G, Beamforming, Grid-of-Beams, Machine learning, Deep learning, Peak finding algorithm, etc.**

I. Introduction

THE Multiple-Input and Multiple-Output (MIMO) techniques are now widely used in cellular systems and have gradually evolved in recent decades, which are expected to reshape the 6G wireless communications and networks. In particular, a base station (or gNodeB, gNB) of 5G New Radio (NR) networks is equipped with a very large number of antennas. They improve the network performances as well as increase the coverages. We call them massive MIMO (mMIMO). The mMIMO will be a key technique in 6G systems. The key challenges to implement mMIMO are to obtain accurate channel state information, reduce overheads, satisfy different variants, and so on. In case of multiuser MIMO, a base station equipped a larger number of antennas than mobile stations (or User Equipment, UE) transmits multiple data streams to mobile stations at the same time. Thus, we can achieve a high throughput. In 5G, beamforming is used to allow for directional multiple beams by weighting magnitude or phase of signals in multiple antennas. It can improve spectral efficiency and reduce interferences. Thus, mobile users can receive strong signals and it is helpful for maintaining faster and more reliable connectivity in 5G systems. In particular, it provides us with a better coverage for an edge user. There are three types of beamforming schemes: Digital beamforming, Analog beamforming and Hybrid beamforming. Digital beamforming uses pre-coding in baseband domain and designs different signals for antennas. Typically, the multiple beams are created by matrix-based operations including weighted amplitudes and phases. It allows us to control multiple beams without a hardware change efficiently and flexibly. In order to implement digital beamforming, separate Radio Frequency (RF) chain per an antenna is assumed. It causes a higher complexity. The other disadvantages are high Direct Current (DC) power, loss signal and so on. Analog beamforming adjusts the phases of each antenna in RF domain and creates an antenna pattern with a specific direction. It brings an impact on the radiation pattern and gain of the antenna. Thus, it improves the coverage as well as creates narrower beamwidths with simple hardware. However, the key disadvantage is the limited number of beams and not flexible beam generation. Hybrid beamforming (also known as hybrid precoding) combines them to balance computational complexity and performance. Coarse beamforming is performed in analog domain and then the analog beams adopt a MIMO scheme in digital domain. It allows us to reduce the number of RF chains and improve the flexibility. It is considered for 5G NR mmWAVE frequency range. Many research groups now pay attention to develop beamforming techniques and efficient beam selection techniques for 6G networks.

In [1], the 3rd Generation Partnership Project (3GPP) defined the beam management procedure for 5G NR for ideal mode and connected mode. The ideal mode is selected when UE does not have active data transmission. The connected mode is used when active data exchange is taking place. The Layer 1 (L1) and Layer 2 (L2) beam management procedure to obtain an optimal beam pair (where a beam pair means a transmit beam and a corresponding receive beam to establish a connection) can be summarized as follows: Step1 is to acquire frame synchronization and find the cell identity. Step 2 is a beam sweep and measurement. In this step, the gNB periodically transmits beams in all directions. The UE detects all beams in a search area and measures the strength of the beams in terms of Reference Signal Received Power (RSRP), Signal-to-Interference-plus-Noise Ratio (SINR) or Reference Signal Received Quality (RSRQ). Step 3 is beam selection and reporting. In this step, the UE selects the beam with the strongest signal, reports it to the gNB, and establishes connectivity. Each cell includes multiple static Synchronization Signal Block (SSB) beams always pointing in the same direction. They form a Grid-of-Beams (GoB) and cover the whole cell area [2, 3, 4]. Different SSBs are transmitted at different time slots in a cell. They minimize intra-cell interferences among SSBs. Thus, the 5G coverage is based on not cells but beams. In order to identify separating beams, Physical Cell ID (PCI) and beam ID are used. SSB beams are regarded as a new layer of mini-cells in each cell.

We mentioned many benefits of MIMO and beamforming techniques but there are still many research challenges to design and implement them. In particular, we need to optimize beam management schemes in terms of beam selection, connection set-up time, energy efficiency, throughput, network outage, QoS/QoE, and so on. It is not easy to find optimal network parameters and keep good link quality. Based on the GoB approach of 3GPP, the UEs do not observe actual channels but low-dimensional effective channels. The orthogonal Reference Signal (RS) is assigned to beam in the GoB codebook [5]. The performance of GoB codebook design is relevant to the reporting of the UE. It is directly related to the precoder selection. Thus, we can reduce the overhead by exploiting effective channels but the overhead reduction causes performance degradation because the reduced channel representations might not include the key characteristics of the real-world channels. In [6], an iterative scheme for beam management is proposed. They removed some beams contributing less to sum-rate of a multi-user MIMO. In [7], the authors proposed a low complexity beam selection using approximation of the sum-rate computed out of the elements of the effective channel matrix at the output of the analog beamforming block. Their approach shows us a near-optimal in the high SNR. The beam training can be divided into initial access and beam tracking. The initial access is to establish an initial connectivity in the absence of channel information. It is required as the first step of beamforming schemes. The beam tracking is performed when a connectivity is maintained. It tracks the deviation of the paths and updates the quality of connectivity. The conventional approach is based on exhaustive search algorithms and codebook designs. There are many algorithms to reduce the training complexity and the overhead cost. In [8], the authors proposed multi-resolution codebooks to reduce the setup time of beamforming. In [9], a low complexity hierarchical codebook based beam alignment is proposed. In [10], a low complexity primary-auxiliary codebook based beam training is proposed. As AI techniques are adopted in many research fields, they will be one of key technologies for 6G. They as game-changers will play a critical role in 6G and re-build cellular networks. In order to adopt AI techniques to 6G, it is important to collect and store enough training data. Fortunately, 6G would be good environment to acquire a big data and operate AI models. Thus, many research groups are exploring AI techniques and adopting them to wireless systems including beamforming [11, 12]. In order to improve the accuracy of beamforming, the extrinsic information such as GPS and Lidar signals is sometimes used for deep learning training [11,12].

The main contributions of this paper can be summarized as follows:

(1) New beam selection method using machine learning and peak finding algorithm is proposed to obtain the optimal beam pair and reduce the beam sweeping overhead.

(2) Performance of the proposed beam selection method is evaluated and analysis and lessons-learned are described.

The remaining parts of this paper are as follows: In section II, system model is described. In section III, a new beam selection method is proposed. In section IV, numerical analysis is introduced, and analysis and lessons-learned are included. Section V contains the conclusion and summary.

II. System Model

We consider a single cell OFDMA based downlink model. Figure 1 illustrates an example of single cell downlink beamforming scenario.

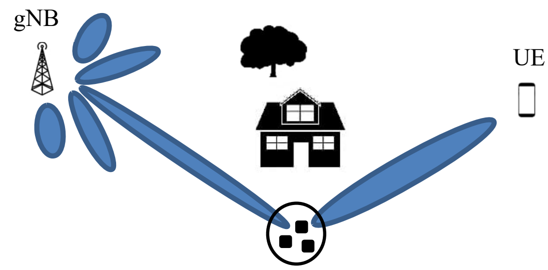

Figure 1 Example of single cell downlink beamforming scenario.

The gNB is equipped with $N_t \gg 1$ antennas and has codebooks

$$B_{gNB} = \left\{\mathbf{v}_1, \dots, \mathbf{v}_{|B_{gNB}|} \middle| \mathbf{v}_i \in \mathbb{C}^{N_t \times 1}\right\} \quad (1)$$

where $\mathbf{v}_i$ denotes ith beamforming vector in B_{gNB}. The gNB serves $K \ll N_t$ UEs with N_r antennas and codebooks

$$B_{UE} = \left\{\mathbf{w}_1, \dots, \mathbf{w}_{|B_{UE}|} \middle| \mathbf{w}_j \in \mathbb{C}^{N_r \times 1}\right\} \quad (2)$$

where $\mathbf{w}_j$ denotes jth beamforming vector in B_{UE}. The channel matrix of the kth UE is $\mathbf{H}_k \in \mathbb{C}^{N_r \times N_t}$. We assume grid-of-beam of 3GPP [1, 3]. The objective of the beam selection is

$$\max_{(i,j)\in|B_{gNB}|\times|B_{UE}|} g(i,j) = \left\|\mathbf{w}_j^H \mathbf{H}_k \mathbf{v}_i\right\|. \quad (3)$$

Typically, we can find the solution by sequential exhaustive search method based on the estimate of $\mathbf{H}_k$. The 3GPP adopted the beam management based on this approach. The overhead of beam alignment is proportional to the channel gain uncertainty. In particular, when we deal with vehicular communications or Unmanned Aerial Vehicle (UAV) communications, the channel coherence time is short and the longer overhead of beam alignment is required. Now, we allocate Resource Elements (RE) of resource grid to Reference Signals (RS) and data. We define the Orthogonal Frequency-Division Multiplexing (OFDM) symbol duration τ and the number of the beam training overhead Δ_{gNB} in B_{gNB}. $\tau\Delta_{gNB}$ and RE - $\tau\Delta_{gNB}$ are assigned to RS and data, respectively. When the kth UE has the number of activated beam Δ_{UE}, the received beam training overhead signal of the kth UE $\mathbf{Y}_k \in \mathbb{C}^{\Delta_{UE}\times\tau}$ can be expressed as follows:

$$\mathbf{Y}_k = \sqrt{\frac{P}{RE}}\mathbf{W}_k^H\mathbf{H}_k\mathbf{V}\mathbf{R} + \mathbf{W}_k^H\mathbf{N} \quad (4)$$

where P is the total transmit power at the gNB, $\mathbf{W}_k$ includes the beamforming vectors corresponding to B_{UE} and represents the kth UE beam training overhead combiner, $\mathbf{V} \in \mathbb{C}^{N_{gNB}\times\Delta_{gNB}}$ includes the beamforming vectors corresponding to B_{gNB} and represents the normalized beam training overhead precoder, $\mathbf{H}_k$ is channel matrix between the gNB and the kth UE, $\mathbf{R} \in \mathbb{C}^{\Delta_{gNB}\times\tau}$ includes the known RSs and has the property $\mathbf{R}\mathbf{R}^{\boldsymbol{H}} = \mathbf{I}_{\Delta_{gNB}}$, and $\mathbf{N} \in \mathbb{C}^{N_{UE}\times\tau}$ is Gaussian noise. The kth UE can estimate the effective channels matrix $\mathbf{H}_k \in \mathbb{C}^{\Delta_{UE}\times\Delta_{gNB}} = \mathbf{W}_k^H\mathbf{H}_k\mathbf{V}$ and report it to the gNB. We assume that each UE has single data stream, the transmitted data vector is expressed as $\mathbf{x} \in \mathbb{C}^{K\times 1} = [x_1, \dots, x_K]$ with $E[\mathbf{x}\mathbf{x}^H] = \mathbf{I}_{\boldsymbol{K}}$. The received data signal of the kth UE y_k can be expressed as follows:

$$y_k = \sqrt{\frac{P}{RE}}\overline{\mathbf{w}}_k^H\overline{\mathbf{H}}_k\overline{\mathbf{V}}\mathbf{x} + \overline{\mathbf{w}}_k^H\overline{\mathbf{n}}_k \quad (5)$$

where $\overline{\mathbf{w}}_k \in \mathbb{C}^{\Delta_{UE}\times 1}$ is the data combiner, $\overline{\mathbf{H}}_k$ is the effective channel matrix, $\overline{\mathbf{V}} \in \mathbb{C}^{\Delta_{gNB}\times K}$ is the normalized data precoder, and $\overline{\mathbf{n}}_k \in \mathbb{C}^{\Delta_{UE}\times 1} = \mathbf{W}_k^H\mathbf{n}_k$.

Conventional beam training method of 3GPP [1, 3, 4] searches all beams as $B_{gNB} = \Delta_{gNB}$. In order to reduce the overhead, we need to search only the relevant channel components and define the set of the relevant beam training overhead D_k for the kth UE in B_{gNB} as follows:

$$\mathrm{D}_k = \left\{(i,j)\middle| E_{\mathbf{H}_{\boldsymbol{k}}}\left[\left|\mathbf{w}_j^H\mathbf{H}_{\boldsymbol{k}}\mathbf{v}_i\right|^2\right] \geq \theta\right\} \quad (6)$$

where θ is a threshold of the power. D_k contains the relevant beam pairs. In [13], the relationship between beam coherence time and channel coherence time is investigated. The channel coherence time T_C is already well defined as the time over which the channel response is not varying. The beam coherence time T_B is defined as the average period over which the beams are unchanged. For a given receive beam, when the received power $P(t)$ is below a ratio $\xi \in [0,1]$ compared to the peak receive power, the receive beam points at the peak direction μ_r at time t and the beam coherent time is defined follows [13]:

$$T_B = \inf_{\gamma}\left\{\gamma\middle|\frac{P(t+\gamma)}{P(t)} < \xi\right\} \quad (7)$$

and the power decrease is caused by the pointing error. D_k only relies on the second order statistics (Correlation properties of wireless channels) of the channel matrix $\mathbf{H}_{\boldsymbol{k}}$. The beam coherence time is much longer than the channel coherence time [14]. When the kth UE beam training overhead combiner $\mathbf{W}_k$ is selected, we can represent the beam selection subset as $\mathrm{D}_k(\mathbf{W}_k)$ that can be regarded as precoding matrix indicator (PMI). In 3GPP [1, 3, 4], the UE reports the desired PMI to the gNB. The PMI report is about what precoding matrix is used for the downlink channel. More specifically, the PMI report is not a matrix but coefficients. The gNB finds weights for beamforming and construct a precoding matrix using the coefficients. The combination of them is limited. Likewise, the kth UE has the second order statistics and report $\mathrm{D}_k(\mathbf{W}_k)$ to the gNB when conventional exhaustive search method is used. In this paper, we assume that $\mathrm{D}_k(\mathbf{W}_k)$ is not specific coefficients but the beam selection subset information. The UEs do not report the PMI and the gNB finds the relevant searching sets in all candidate sets $\bigcup_{k=1}^{K}\mathrm{D}_k(\mathbf{W}_k)$ using machine learning algorithms. We target to minimize the overhead and find the optimal beam pairs.

There are many ways to design the precoders such as Minimum Mean Square Error (MMSE), Matched Filtering (MF) and Zero Forcing (ZF). The ZF precoder as one of popular techniques creates orthogonal channels for each UE and applies transformation matrix to the transmit signal. We assume that the gNB uses the ZF precoder and UE has a single receive beam such as $\Delta_{UE} = 1$. Thus, we can simplify the effective channel matrix $\overline{\mathbf{H}}_k \in \mathbb{C}^{K\times\Delta_{gNB}}$ between the gNB and the kth UE as follows:

$$\overline{\mathbf{H}}_k = \left[\overline{\mathbf{h}}_1^T, \dots, \overline{\mathbf{h}}_K^T\right]^T \quad (8)$$

where $\overline{\mathbf{h}}_k = \mathbf{w}_k^H\mathbf{H}_{\boldsymbol{k}}\mathbf{V}$. We can rewrite (5) as follows:

$$y_k = \sqrt{\frac{P}{RE}}\rho\overline{\mathbf{H}}_k\overline{\mathbf{V}}_{\boldsymbol{ZF}}\mathbf{x} + \mathbf{n} \quad (9)$$

where $\overline{\mathbf{V}}_{\boldsymbol{ZF}} \in \mathbb{C}^{\Delta_{gNB}\times K}$ is ZF precoder and ρ is the power normalization factor. Now, we can define the optimal beam allocation at the gNB using the maximum sum-rate criterion [14] as follows:

$$g^*(\mathbf{w}_k) = \underset{\mathbf{W}_k}{\operatorname{argmax}}\sum_{k=1}^{K}\log_2(1+\zeta_{k,\mathbf{w}_k}) \quad (10)$$

where $\zeta_{k,\mathbf{W}_k}$ denotes the beam strength at the kth UE for the beam selection $\mathbf{w}_k$. The beam strength can be RSRP, RSRQ or SINR. If the channel state information is fully known, the optimization problem (10) can be solved by an exhaustive search method with the complexity $O(\mathbf{W}_k)$. The complexity increases exponentially as the number of user K increases.

III. Proposed Two Stages Beam Selection Method

In section II, we constructed the system model based on the GoB and PMI of 3GPP 5G NR. In this section, we propose two stages beam selection method consisting of machine learning and peak finding algorithm to reduce beam sweeping overhead.

A. Outline for two stages beam selection method

The beam selection of 5G NR is based on the exhaustive search method systematically checking all possible candidates whether or not they satisfy the statement of the problem. The beam selection subset $\mathrm{D}_k(\mathbf{W}_k)$ as a PMI is regularly reported to the gNB. The exhaustive search method results in a long beam search time, a high overhead cost, and a high energy consumption. In this paper, we improve the beam selection process using machine learning and peak finding algorithm. In the first stage, we find the beam selection subset $\mathrm{D}_k(\mathbf{W}_k)$ using machine learning from a history data set. Therefore, the UEs do not report all of PMI information regularly. The overhead cost can be reduced. In the second stage, we search the optimal beam pair from the beam selection subset $\mathrm{D}_k(\mathbf{W}_k)$ by peak finding algorithm. The proposed two stages beam selection algorithm is described in the next sections.

B. Beam selection subset using machine learning

The optimal beam allocation problem (10) can be regarded as classification problem of machine learning. We can have a labeled data set as a pair of $(\mathbf{w}_k, g^*(\mathbf{w}_k))$ and construct a neural network consisting of the input nodes of $\mathbf{w}_k$ and the output nodes of $g^*(\mathbf{w}_k)$. We find the optimal beam allocation $g^*(\mathbf{w}_k)$ for the given input $\mathbf{w}_k$ that is equivalent to solve the problem (10). The beam selection is mapped into the pair. The input vector is the beam forming vector of the UE. The input layer is constructed accordingly. In the hidden layers, the neurons are fully connected to all activations in the previous layer. In addition to them, Softmax layer, normalization layers and dropout layers are added. Softmax layer is located in the end of fully connected layer. Softmax layer is used for multi-classification. In the output layer, the output of Softmax layer corresponds to an estimate of the optimal beam allocation. The neural network model is trained by history data about the location of UEs and the true optimal beam pairs. The training data set is generated as following steps: Step 1. Generation of the received signals in terms of UE locations and signal strength, Step 2. Collection of the true optimal beam pairs by searching exhaustive method over all beam pairs, Step 3. Formulation of the labelled data set from the true optimal beam pairs. Using the trained neural network, we search the beam selection subset, predict the beam pairs with the high beam strengths, and find the beam selection subset $\mathrm{D}_k(\mathbf{W}_k)$ in the test phase. Figure 2 illustrates the neural network structure to find the beam selection subset.

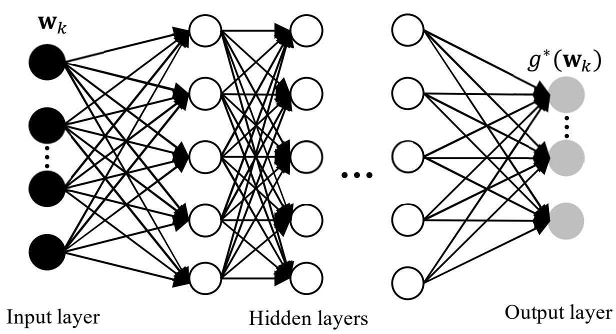

Figure 2 Neural network to find the beam selection subset.

As another machine learning method, we consider K-nearest neighbours (KNN) algorithm where K denotes the nearest neighbour data points (Note, the "K" of KNN is the name of the algorithm and not related to the number of UEs in this paper). The KNN is simple but powerful to solve both classification and regression problems. It has flexible decision boundaries and is robust to noisy training data. Likewise, we consider the labelled dataset as a pair of $(\mathbf{w}_k, g^*(\mathbf{w}_k))$. The value of the target function for a test data set is estimated from the known value of the nearest training data. The input $\mathbf{w}_k$ and its nearest neighbour $\mathbf{w}_k{}'$ satisfies

$$\mathbf{w}_k{}' = \arg\min_{\mathbf{w}_l} dist\,(\mathbf{w}_k, \mathbf{w}_l) \quad (11)$$

where $dist$ () is Euclidean distance and $k \neq l$. In the NN classification model, we consider a Euclidean distance and compute the decision boundaries. The decision boundary between any two data points is a straight line. It shows us how input space is divided into classes. The pseudocode of KNN algorithm can be summarized as follows:

Procedure KNN algorithm
Load the training and test data
Choose the value of κ *// where κ is the nearest neighbours and a small positive integer.*
for Each data point in test data
- Compute the Euclidean distances between the query data points and all training data points
- Store and sort the Euclidean distances
- Choose the first κ points
- Assign a class to the test data point by majority vote

end
return $g^*(\mathbf{w}_k)$.

C. Optimal beam pair selection using peak finding algorithm

After finding the beam selection subset $\mathrm{D}_k(\mathbf{W}_k)$ by machine learning, (10) can be rewritten as follows:

$$g^*(\mathbf{w}_k) = \underset{\mathrm{D}_k(\mathbf{W}_k)}{\operatorname{argmax}} \sum_{k=1}^{K} \log_2(1 + \zeta_{k,\mathrm{D}_k(\mathbf{W}_k)}) \quad (12)$$

where $\zeta_{k,\mathrm{D}_k(\mathbf{W}_k)}$ denotes the beam strength at the kth UE for the beam selection $\mathbf{w}_k$ in the subset $\mathrm{D}_k(\mathbf{W}_k)$. The complexity of the optimization problem (12) by an exhaustive search is $O(\mathrm{D}_k(\mathbf{W}_k))$. If we reduce the candidates in the beam selection subset $\mathrm{D}_k(\mathbf{W}_k)$, the complexity will decrease significantly. Now, we need to select the final beam pair in the subset. Since the size of the subset is not large, the simple peak finding algorithm would be more fit and guarantee the optimal beam pair $(\mathbf{w}_k, g^*(\mathbf{w}_k))$. One of simple peak finding algorithms is divide-and-conquer method. Firstly, we divide the problem into multiple sub-problems that are smaller datasets. Secondly, we solve the subproblems iteratively and find them until subproblems are small enough. Lastly, we combine the results to solve the original problem. The pseudocode of peak finding algorithm can be summarized as follows:

Procedure Peak finding algorithm
Load the beam selection subset $\mathrm{D}_k(\mathbf{W}_k)$ where k is [1,…K]
Define $m = \lfloor K/2 \rfloor$
for Each data point
  if $\mathrm{D}_k(m-1) \leq \mathrm{D}_k(m) \geq \mathrm{D}_k(m+1)$
    return m
  elseif $\mathrm{D}_k(m-1) > \mathrm{D}_k(m)$ **then**
    return find a peak in $\mathrm{D}_k(1, m-1)$
  elseif $\mathrm{D}_k(m) < \mathrm{D}_k(m+1)$ **then**
    return find a peak in $\mathrm{D}_k(m+1, K)$
  until One element left in the subset
end

IV. NUMERICAL ANALYSIS

As we describe system model in section 2, we consider single cell downlink model and formulate the beam selection problem based on GoB and PMI of 3GPP 5G NR. Using a beamforming toolbox and a machine learning toolbox of Matlab [15], we evaluate the performance of the proposed two stages beam selection method and compare with conventional exhaustive search method. The key simulation configurations are summarized in table 1.

Table 1. Simulation configuration

Parameters	Values
Number of cells and transmission	Single cell downlink
Frequency range	FR1 (Sub 6 Hz)
Channel model	MIMO scattering channel with 10 scatterers
Transmitted SSBs	8
Synchronization Signal Block (SSB)	Case B for FR1
Period of the SS burst	20ms
Subcarrier spacing	15kHz
Centre frequency	2.5GHz
Transmit/Receive antenna size	8x8 (Tx) / 2x2 (Rx)
SNR	30dB
Measurement mode for SSB	Only secondary synchronization signals (SSS)
Number of scatterers	10
Total number of beam pairs	16
Number of different receiver locations in training dataset/ test dataset	200 (Training)/100 (Test)
Neural network structure	1 input layer, 4 hidden layers with 96 nodes and ReLU activation function, 1 output layer with Softmax layer
The value of κ of KNN	1 - 16
Beam strength metric	RSRP
Max number of iterations	1000

A. Simulation results

In the first simulation, we evaluate the effectiveness of the machine learning algorithms as the beam selection subset finder. According to the size of the beam selection subset, the accuracy of the optimal beam selection is evaluated using the metric of top k accuracy. Figure 3 illustrates the accuracy of the beam pair selection methods using deep learning and KNN in terms of the size of the beam selection subset.

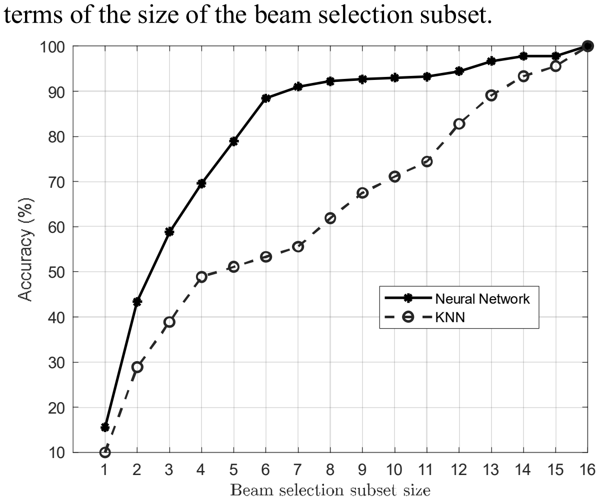

Figure 3 Accuracy of the beam pair selection.

As we can observe the figure 3, when the beam selection subset size is 7, the accuracy (%) of the deep learning and KNN is more than 90% and 55%, respectively. This result represents that the trained neural network is useful for finding beam selection subset and reduce the overhead cost caused by beam sweeping. On the other hands, KNN is not much accurate to find beam selection subset. When the subset size is 16 (this is identical to the exhaustive search method), the accuracy of machine learning algorithms is same as the exhaustive search method.

In the second simulation, we evaluate how much the proposed two stage beam selection method is effective. In order to compare with the exhaustive search method, we compute the average RSRP (dB) of the selected beam pairs when different beam selection methods are used (Note. the value of RSRP is typically represented in dBm. However, the purpose of this simulation is to compare their performances. It is represented in dB.). Figure 4 illustrates average RSRP of the selection beam pairs by different beam selection methods.

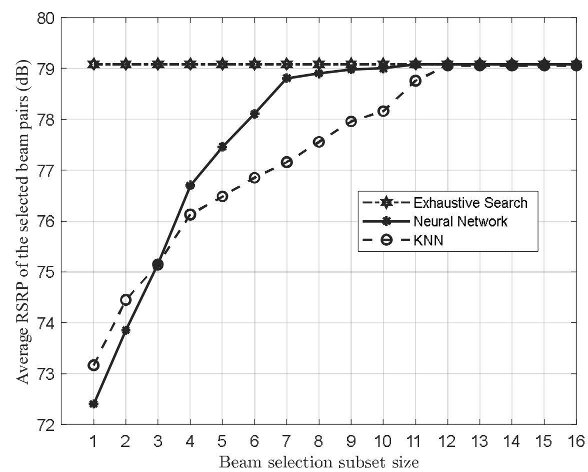

Figure 4 Average RSRP of the selected beam pairs by different beam selection methods.

As we can observe figure 4, when the beam select subset size is more than 7, the average RSRP of the selected beam pairs of deep learning is close to the exhaustive search method.

B. Analysis and lessons-learned

From the first simulation, the effectiveness of the neural network to find the beam selection subset is verified. The neural network model trained by the historical data is useful for finding the optimal beam pair. Under the given simulation configuration, the beam selection subset size should be larger than 7. If we use the neural network, we can find the optimal beam pair in 44% (=7/16) of the total beam pairs and reduce the overhead cost. From the second simulation, we confirm that the proposed two stages beam selection method finds the optimal beam pair well from only 44% beam pair sets. However, another simple machine learning method KNN does not work well. In addition, we need additional computation to train the neural network model.

One important lessons-learned of this research work is how training of neural network affects to the performance. The MIMO scattering channel model in this simulation is based on a multipath propagation channel depending on time delay, gain, Doppler shift, phase offset, atmospheric loss and so on. The performance of accuracy is varying depending on the channel realizations and different system parameters. The trained neural network doesn't work well under the different channel conditions and system configurations. In particular, the coherence time should be maintained to have good level of performance. If the channel is not static, the trained neural network model is not effective, and the accuracy is significantly low. In order to apply the proposed method for a beamforming system, the channel should be treated as constant. Thus, we should consider both a channel coherent time and a beam coherence time and design the beamforming operation. We can design signalling of the proposed two stages beam selection method as shown in figure 5.

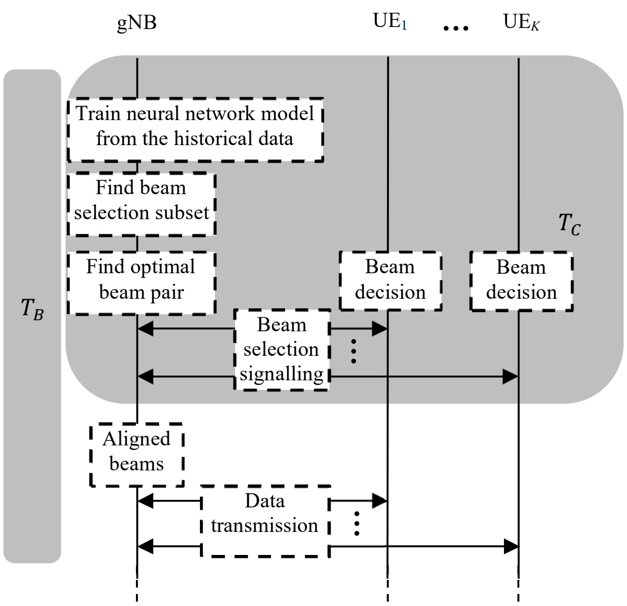

Figure 5 Signalling of the proposed two-stages beam selection method with restrictions of coherence times.

As we can observe figure 5, the channel coherence time should be maintained during the proposed beam selection method and the data between gNB and UEs are stably transmitted during the beam coherence time.

V. Conclusion and Summary

In this paper, we proposed two stages beam selection method consisting of machine learning and peak finding algorithm to reduce the beam sweeping overhead. The exhaustive search method of the 3GPP 5G NR causes a long beam search time, a high overhead cost, and a high energy consumption. The proposed beam selection method is predicting the beam selection subset by machine learning and then finding the optimal beam pair from only 44% of the searching set. Thus, the UEs do not need to report all PMI information regularly and the beam sweeping overhead can be reduced. By numerical analysis, we showed that the trained neural network model is useful for finding the beam selection subset and the proposed two stages beam selection method finds the optimal beam pair well. However, the accuracy to predict the beam selection subset is varying in terms to coherent times and system parameters. Thus, future works are to investigate online learning methods of neural networks to satisfy the restriction of coherence times as well as design the refined signalling.

Acknowledgement

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