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AI-Based Beam Management in 3GPP: Optimizing Data Collection Time Window for Temporal Beam Prediction

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ABSTRACT Artificial Intelligence (AI) has gained significant attention and extensive research across various fields in recent years. In the realm of wireless communication, researchers are exploring the use of AI to facilitate various physical layer (PHY) procedures. Within the standardization efforts of the Third Generation Partnership Project (3GPP), one prominent direction being explored is AI-based beam management (BM). The primary objective is to harness AI techniques for predicting optimal beams, thereby reducing measurement overhead and latency. This paper aims to discuss the progress made in AI-based beam management within the Release 18 standardization. Furthermore, through our research, we have identified the mobile speed of user equipment (UE) as a crucial factor that impacts the optimal time window size for collecting input data in AI models. We have observed an inverse correlation between UE speed and the time window size. Accordingly, to mitigate unnecessary measurement overhead and latency, we propose that the determination of the time window size for input data collection should be based on the UE speed. Additionally, we will present our simulation results and provide a comprehensive analysis of this relationship.

INDEX TERMS Artificial intelligence, third generation partnership project (3GPP), beam management, the mobile speed of user equipment, optimal time window size.

I. INTRODUCTION

With the increasing number of antenna arrays in millimeter-wave technology, it has become more feasible and flexible to enhance the quality of wireless communication links through beam management. Hybrid beam management, which includes analog beamforming and digital precoding, is adopted in 5G New Radio (NR). However, within the 3GPP framework, the beam management process exclusively focuses on analog beamforming—a topic that will also be explored in this paper. The conventional mechanism of beam management (BM) entails a complex procedure involving exhaustive sweeping to select candidate beams. To mitigate measurement overhead and latency, AI has been introduced in 3GPP for BM. In the Radio Access Network Working Group 1 (RAN1), two main sub-use cases for AI-based BM have been discussed. BM-Case1 focuses on spatial-domain downlink (DL) beam prediction based on measurement results from a set of beams. BM-Case2 is temporal DL beam prediction by using historical measurement results from a set of beams [1]. While other use cases have been proposed by companies, due to the difficulty in reaching a consensus among the companies, only these two use cases for BM have been retained for further study at this stage. We will share the details for the progress of above mentions in 3GPP at next section.

With the development of AI technology that has also made significant advancements in other aspects of the physical layer in wireless communication [2], including channel estimation, reference signal (RS) reduction, channel coding, random access, channel state information (CSI) feedback, and positioning. For example, [3] exploits deep learning for positioning, utilizing CSI as the model input to enhance positioning performance in indoor scenarios. [4] proposes the use of deep learning algorithms for channel estimation, considering the time-frequency channel response as a 2-dimensional (2D) image and exploiting pilot values from known locations to estimate unknown channel characteristics, thus reducing the need for physical RS resources to some extent. [5] suggests employing deep learning for massive Multiple-Input Multiple-Output (MIMO) CSI feedback and introduces CsiNet, a framework that learns a transformation from CSI to a codeword and an inverse transformation from the codeword to CSI, thereby reducing feedback overhead. In [6], deep neural networks are proposed for decoding polar-coded short packets. AI-based channel coding is also a future challenge in wireless communication, as it aims to achieve lower latency and higher reliability by using AI. In the context of nonorthogonal random access (NORA), [7] proposes deep learning-based power control schemes to enhance NORA performance.

Regarding the AI-based BM, there are also some research findings, [8] proposes a method for generating a training set for high-speed applications. It utilizes the current RS to measure the reference signal received power (RSRP) and absolute arrival time, which serve as training data and yield improved accuracy in beam prediction. [9] presents a methodology for generating 5G propagation channel data for machine learning. It combines a vehicle traffic simulator with a ray-tracing simulator to generate channel data for 5G scenarios with mobility, which is used for beam selection. [10] introduced deep learning for beam management and interference coordination, developing a deep neural network to replace complex conventional algorithms and significantly reduce computational complexity and latency. [11] proposes a scheme to infer probable candidates of optimal beams by utilizing the power delay profile (PDP) of sub-6GHz channels as input for the AI model. PDP is a critical parameter for channel characteristics, which not only improves the gain of beam selection but also provides great benefits for AI-based positioning that is also a highly anticipated direction in 3GPP. In [12], it proposes that using machine learning for intra cell beam handovers in mmWave 5GNR system. It develops a base station centric approach for predicting the Signal-to-Noise-Ratio (SNR) of beams. And then based on SNR difference between the serving and target beams a handover can be decided, where the target beams are obtained from the prediction results.

In this paper, we will discuss the progress of some proposals that have received significant attention in 3GPP on AI-based BM. Additionally, the main focus of this paper is on BM-Case 2. In BM-Case 2, historical beams need to be measured for AI model input, which poses a problem: How long should the historical time be chosen? In other words, how do we determine the time window size for data collection? Actually, some fixed values (40 ms, 80 ms, 160 ms, 320 ms, 640 ms) have been agreed upon by companies for collecting measurement results to evaluate the performance of the AI model in 3GPP. In this study, we will analyze the factors affecting the selection of the input data collection time window size and provide simulation results to support our perspective: adjusting this value based on UE speed offers flexibility, minimizing unnecessary measurement overhead and latency.

II. THE STANDARDIZATION PROGRESS OF AI-BASED BM

AI-based BM involves three significant aspects to be discussed, i.e., model training, model inference and model monitoring, and we will elaborate on the progress made in specifying these crucial parts in 3GPP.

A. MODEL TRAINING

Data collection plays a pivotal role in model training, encompassing numerous intricate details that require careful design. These details include content, type, and quality, among others.

In the AI-based BM, companies have collaborated to reach agreements on model inputs, specifically focusing on three alternatives: L1-RSRP alone, L1-RSRP with assistance information, and L1-RSRP with corresponding beam ID. These alternatives are considered for both BM-Case1 and BM-Case2. Additionally, an exclusive input option for BM-Case1 is the channel impulse response (CIR). Primarily, most companies prefer using L1-RSRP as the input for AI models. This approach minimizes the impact on current specifications. If the input and output being identical means using historical beams to predict future beams with the same index, collecting beam IDs may not be necessary. A sufficient collection of LI-RSRP measurements, with a specific order, would be adequate. Furthermore, it might be possible to differentiate the beams using alternative information, such as beam angles, instead of relying solely on beam IDs. In other words, if the beam angles are clearly defined, collecting beam IDs becomes unnecessary. Some companies even evaluate the performance of AI models using beam angles as assistance information, which can provide significant benefits. However, opponents raise concerns about how to obtain the beam angle and whether it entails vendors' privacy information. If obtaining beam angle-related information proves challenging, collecting beam IDs becomes necessary for labeling each beam. As for CIR, based on simulations conducted by some companies, it has been shown that it can bring great benefits for beam prediction. However, the complexity is also increasing, and perhaps new reference signaling needs to be designed for it.

The inclusion of other assistance information to enhance beam prediction accuracy remains a highly debated topic in RAN1. After extensive rounds of discussions, certain assistance information, such as the UE moving direction and UE location, has demonstrated considerable benefits. However, due to privacy concerns, the collection and reporting of such information to gNB are not supported by 3GPP.

Regarding data quality, the quantizing precision of L1-RSRP is a decisive factor highlighted by some companies. Training the AI model with a higher level of precision in L1-RSRP quantization leads to improved performance. However, deploying the model on the network side incurs substantial reporting costs, and its feasibility also relies on the capabilities of UE. Some UEs may not possess the capability to achieve higher quantizing precision. As a result, striking a balance

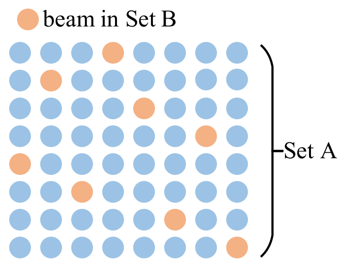

FIGURE 1. Set B is a subset of set A.

between performance and overhead becomes a trade-off in this context. It is important to note that reaching a definitive conclusion regarding this matter may not be achievable during the SI stage.

B. MODEL INFERENCE

Utilizing AI to infer candidate beams and replace the legacy beam management mechanism is our primary objective. However, the question of what should constitute the output of AI has sparked extensive deliberation. Initially, RAN1 summarized three alternatives for studying predicted beams: DL Tx beam prediction, DL Rx beam prediction, and DL beam pair prediction. In conventional BM mechanism, the selection of the optimal DL Rx beam is left to the UE's implementation, prompting certain companies to question the necessity of studying DL Rx beam prediction. When DL Rx prediction is enabled, it necessitates the reporting of Rx beam-related information, thereby leading to substantial modifications in the existing specification. As a result, DL Rx beam prediction has been granted a lower priority during the SI stage. In the meantime, to circumvent the aforementioned challenges, 3GPP exclusively supports the UE-side model for DL beam pair prediction.

In order to facilitate further discussion, it is crucial to consider two vital concepts. Firstly, a set encompassing all possible DL beams, known as Set A, includes the predicted beams. Secondly, Set B consists of the measured beams used as input for the AI model. It is important to clarify the relationship between Set B and Set A for both BM-Case1 and BM-Case2. The main driving force behind employing AI for beam prediction is the reduction of measurement overhead and latency. Therefore, most companies advocate for Set B to be a subset of Set A. As depicted in Fig. 1, it can be a pattern of Set B, which consists of only eight beams, these beams have been randomly selected from Set A. The UE only needs to measure these eight beams as input for the AI model, facilitating the prediction of the N/top-N beams.

Based on the ongoing discussions within 3GPP, the pattern of Set B can be random, fixed, or pre-configured. As of now, 3GPP does not restrict the algorithms for choosing the Set B pattern. Furthermore, this choice may depend on the implementation of the AI model as well as the capabilities of UE. Moreover, alternative approaches exist for the relationship between Set B and Set A. For instance, one option is to utilize the measurement results of wide beams to predict N/top-N narrow beams, resulting in Set B and Set A being different entities. Additionally, for BM-Case2, Set A and Set B being the same is also supported in the SI stage.

The criteria for selecting the N predicted beams proposed by companies exhibit notable divergence. Some companies endorse the summation of probabilities surpassing a certain threshold to identify the best beams, while others suggest choosing beams based on maximum dwelling time or maximum L1-RSRP. Nevertheless, the specific criteria employed for the AI model's output seem to have limited impact on the specification. This is due to the fact that the gNB/UE simply needs to acquire the candidate beams and organizing the candidate beam IDs in a specific order proves sufficient. Reporting or indicating probabilities, dwelling time, L1-RSRP, and other information remains optional.

C. MODEL MONITORING

The performance of the AI model needs to be monitored in its life cycle management (LCM). Based on the monitoring results, various operations, such as model selection, model activation, model deactivation, model switching, and fallback, are carried out. After the purpose of monitoring is clarified, two questions need to be addressed: who is responsible for making decisions regarding these operations, and what metric should be used to evaluate the performance of the AI model?

Considering monitoring the UE-side model, 3GPP provides support for three options: NW-side model monitoring, UE-side model monitoring, and hybrid model monitoring. These options determine which side is responsible for calculating the performance metric and making decisions regarding the aforementioned operations. For example, in the case of NW-side model monitoring, the NW is responsible for calculating the performance metric based on UE reporting and making decisions related to model selection, activation, deactivation, switching, and fallback operations. Regarding hybrid model monitoring, the UE calculates the performance metric and reports the results to the NW, and then the NW makes the decision. For the NW-side model, only NW-side model monitoring is supported, as companies consider it unreasonable for the UE to manage the NW-side model.

Several options were explored as performance metrics for model monitoring with potential down-selection. These options include beam prediction accuracy, link quality, data distribution of input and output of the AI model, and L1-RSRP difference evaluated by comparing measured RSRP and predicted RSRP. The actual best beam should be obtained and compared with the predicted best beam when the beam prediction accuracy is applied for monitoring. However, the conventional exhaustive beam sweeping method becomes unavoidable to obtain the actual best beam, resulting in increased overhead, particularly for periodic monitoring. Evaluating link quality may not provide a clear assessment of the AI model's performance since poor link quality may not be caused by predicted beams, but it may simply serve as

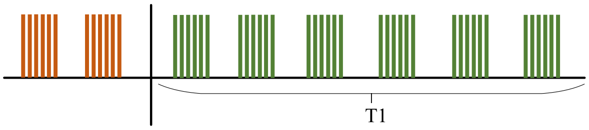

FIGURE 2. Period of data collection in the time domain.

a trigger condition for monitoring. Extracting the data distribution feature from the AI model's input and output requires extensive data collection, making it more suitable for model validation during the training stage rather than the monitoring stage. When we take both cost and performance into consideration and try to balance them, the L1-RSRP difference is a more appropriate metric. By measuring the beams based on the predicted results instead of full set, the complexity and overhead associated with this approach become more acceptable compared to the other options.

III. INFLUENCE OF UE SPEED ON BM-CASE2

In BM-Case2, the beams for future time instances are predicted by utilizing the measurement results of multiple historic time instances. It can be understood that the AI model employed in BM-Case2 operates in the time domain. When collecting data for BM-Case2, timestamps are also taken into account. The AI model needs to determine whether the data are still valid or have expired. As depicted in Fig. 2, for each prediction instance, UE measures the beams within T1 as inputs for the AI model. The beams beyond T1 might not provide significant assistance or might be less relevant to the current prediction instance. We can interpret the data obtained from the green beams as valuable and effective, whereas the data from the red beams are outdated.

Therefore, it is essential to investigate the optimal time window size for collecting input data to minimize unnecessary measurement overhead. As the described above, when the data collection period exceeds the optimal time window size, extra data may not contribute significantly to improving the prediction accuracy, even it is possible that as the data collection period increases, the prediction accuracy may have already reached a plateau. For example, if collecting data from the past six seconds achieves an 80% prediction accuracy for the AI model, extending the duration to eight seconds may still yield the same 80% accuracy. Hence, data beyond the time window not only prove useless for beam prediction but also increase overhead and latency.

The characteristics of the time domain channel play a crucial role in determining the optimal time window size for the model input, and one important factor in assessing these characteristics is the UE speed. High-speed UE induces a fast-fading state in the channel, while low-speed UE results in a slow-fading state. The coherent time of the channel has an inverse relationship with UE speed, meaning that the fast-fading channel has a shorter coherent time compared to the slow-fading channel. To achieve better performance of the AI model, it is desirable for the input and output data to exhibit

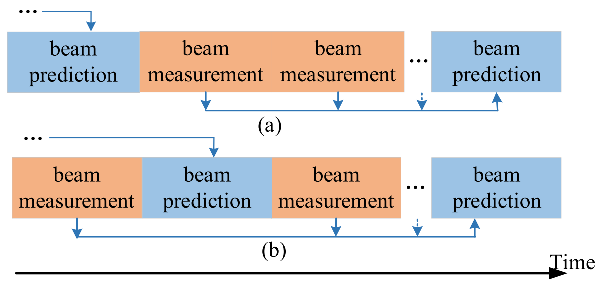

FIGURE 3. Pattern for the historical beam measurement time instances of the model input in BM-case2.

a strong correlation. As we are aware, attaining better performance of an AI model relies on a robust correlation between the input and output data. Ideally, it is expected that the input and output are in a coherent period and that collecting data beyond the coherence time has minimal impact on this prediction instance. Therefore, the optimal time window size for collecting input data will be smaller in a fast-fading channel than in a slow-fading channel. Accordingly, we can determine the optimal time window size for data collection based on the UE speed. When the UE speed is increasing, the time window can be shrunk to avoid unnecessary measurement overhead. Although 3GPP hasn't reached a consensus on UE reporting speed to gNB, it can still be derived by estimating existing reference signals for gNB-side model, such as the demodulation reference signal.

Another issue that needs to be considered when determining the size of the time window is whether the data collected within a certain period can meet the requirements for applying an AI model. This depends on the specific application conditions of the AI model. Currently, the detailed information regarding the application conditions of an AI model is not very clear in 3GPP. However, we can be certain that the Set A/Set B configuration and the content of assistance information should be included. In BM-Case2, two types of patterns are used for selecting historical time instances for measurement, which can be illustrated in Fig. 3. Fig. 3(a) demonstrates measurement results from continuous historic time instances within a period, while Fig. 3(b) shows results from discontinuous historic time instances. Patterns (a) and (b) represent two approaches for selecting past time instances for beam measurement. When the time window size is determined, pattern (a) can provide more data for the input of the AI model compared to pattern (b). However, the measurement overhead in pattern (b) is lower than that in pattern (a). Hence, the choice of the optimal pattern can be flexible. When the length of time for data collection is sufficient, sparse measurement time instances are definitely expected to reduce overhead. For example, within the time window, six measurement instances can be performed, but if the AI model does not require a significant amount of input data, it is unnecessary to measure all six instances in order to save overhead. However, if the size of the time window become smaller, tight measurement

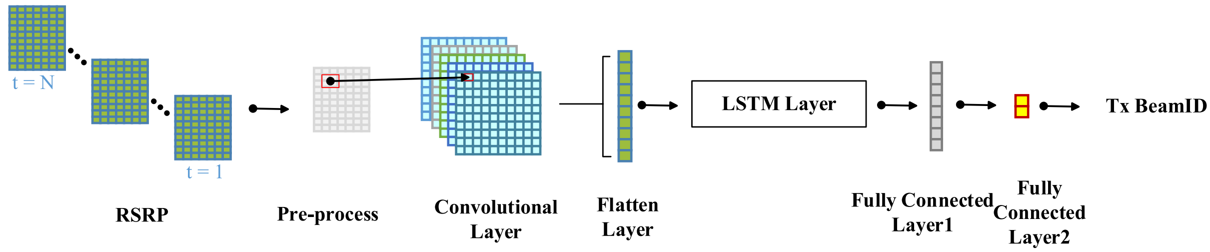

FIGURE 4. Network architecture.

TABLE 1. Hyperparameters of the Network

Hyperparameters	Values
Activation Function	ReLU
Optimizer	Adam
Decay rate	0.25
Batch size	64
Epoch	200
Kernel size	3 × 3
Initial learning rate	0.1
Loss function	RMSE

instances are needed to guarantee the accuracy of beam prediction.

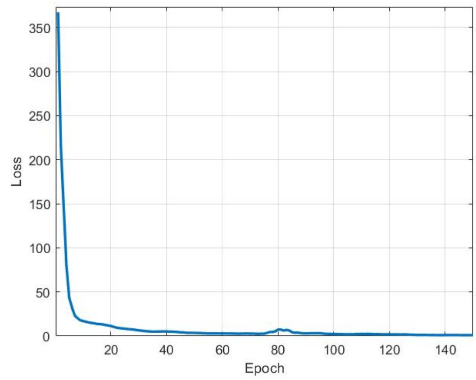

FIGURE 5. RMSE versus Epochs.

IV. SIMULATION AND ANALYSIS

According to our research, our point is that UE speed has a significant impact on determining the optimal time window size for collecting input data; as UE speed increases, the time window size diminishes accordingly. Meanwhile, we perform some simulations to demonstrate our perspective.

A. RSRP-FINGERPRINTING BEAMFORMING NETWORK

In this section, we design a neural network to predict the optimal beam ID based on the RSRP. The network, depicted in Fig. 4, comprises various layers, including an input layer, a 2D convolutional layer, a flatten layer, a long short-term memory (LSTM) layer, a fully connected layer, and a regression layer. The rectified linear unit (ReLU) activation function is employed within this network for enhanced performance. To accelerate the training speed, a batch normalization technique is employed, where each input channel is normalized across a small batch. The hyperparameters used in training the network are summarized in Table 1.

The convolutional layer initially performs convolution on the input using a 3 × 3 convolutional filter to extract meaningful feature information. The extracted features are then flattened into a 1-dimensional feature vector. This vector is inputted to the subsequent LSTM layer, where further compression and extraction of features take place. The LSTM layer also captures the temporal information of the input feature sequence. Following the LSTM layer, the feature vector is passed through a fully connected layer, which enables the network to learn complex relationships between features. Finally, the regression layer is used to predict the best beam ID for the receiving end and the best beam ID for the transmitting end.

During the training phase, the network updates its parameters (i.e., weights and biases) automatically by minimizing the root mean square error (RMSE) loss. RMSE is calculated using (1). In the equation, N represents the total number of samples, which corresponds to the length of the feature sequence. d denotes the actual best beam ID, where the actual best beam is obtained by conventional beam sweeping, and $\hat{d}$ denotes the predicted best beam ID. In this paper's simulation, DL Tx beams are transmitted sequentially according to their beam IDs. Consequently, the RMSE between the predicted best beam and the actual best beam can serve to measure the disparity between predicted and true values. A higher RMSE value indicates a weaker predictive performance of the AI model.

$$RMSE = \sqrt{\frac{1}{N}\sum\nolimits_{n=1}^{N}\left(d-\hat{d}\right)^2} \tag{1}$$

The network takes a 1 × 8 × 32 matrix as input. The output consists of 2 neurons, representing the best beam ID for the receiving end and the best beam ID for the transmitting end, respectively, to facilitate the learning process. The training process of the network is illustrated in Fig. 5.

B. SIMULATION ASSUMPTION AND RESULTS

Regarding the UE trajectory model has been discussed in 3GPP using to evaluate the performance of the AI model. Three options have already been captured in TR38.843 [1]. Option 1 is a linear trajectory model with random direction

TABLE 2. Simulation Procedure

Algorithm 1: **Data collection time optimization in AI-based BM**

% Random UE trajectory model generation:
begin:
input: UE forward range D_f, the width of the road where the UE is located W_r, the number of UE path segment n_{path}, the step number of each segment of the UE path $S_{num} = [s_1, s_2, \ldots, s_{n_{path}}]$.
output: UE location log with time index l_{UE}, UE steering direction with time index d_{UE}.
end
% Beam sweeping result generation:
begin:
initialization: location of BS and scatters: l_{BS}, l_{Sc}, transmitted SNR γ.
input: UE location log and steering direction log l_{UE} and d_{UE}.
output: RSRP matrix log R with all Tx and Rx beams, ID and direction log of best beam pair: b_{ID}, $b_{\mathrm{Direction}}$.
end
% AI-based BM and time window optimization
begin:
initialization: construct the training dataset $\mathcal{S}$, the data is RSRP matrix R, and the label is ID of best beam pair b_{ID}. Divide the training dataset equally into N parts.
for: $p = 1$ *to* N **do**
Extract the pth part of $\mathcal{S}$ for AI model training, where 90% of data is used for training and 10% for testing
Obtain the RMSE of the prediction result of pth part of $\mathcal{S}$.
end for
% Time window optimization
Compare the predictions of different part data and observe the decline of RMSE over time window growth.
Extract the time window when RMSE does not decrease significantly with the growth of the time window length, and the optimization flow is completed.
end

change; option 2 is a linear trajectory model with random and smooth direction change; option 3 is random direction straight-line trajectories. In this section, option 2 is used for this simulation. UE changes direction randomly within [−30°, 30°]. In this study, we evaluate our proposal using the Synchronization Signal Block (SSB). Set A and Set B are identical. At the gNB side, 32 DL Tx beams are generated, and the UE employs 8 DL Rx beams to sweep all of them. Consequently, there are 32 × 8 beam pairs that require measurement during each sweeping period. In our simulation, each sweeping period lasts 160 milliseconds. During the UE movement, we collect 3112 data points. At each point, the UE takes 160 milliseconds to perform exhaustive sweeping. The dataset is created based on these observations. The dataset is partitioned into multiple sub-datasets. Increasing the number of sub-datasets extends the historical data volume, which, in turn, increases the time window size for data collection. Table 2 provides a fundamental overview of the simulation methodology employed in this paper, aimed at facilitating replicable research.

The simulation assumption is shown in Table 3. 4 km/h, 8 km/h, and 16 km/h are considered to evaluate the diverse impact of UE speed on determining the time window size for collecting input data.

TABLE 3. Simulation Assumptions

Parameters	Values
Carrier frequency	28 GHz
Subcarrier spacing	240KHz
System BW	200 MHz
Antenna configuration at BS	[8, 8]
Antenna configuration at UE	[2, 2]
reference signal	SSB
Channel mode	Scattering MIMO Channel
UE speed	4 km/h, 8 km/h, 16 km/h
signal-to-noise ratio	30 dB

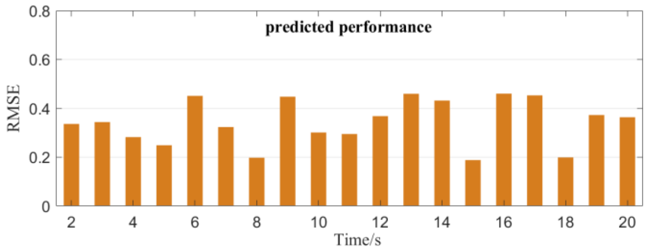

FIGURE 6. Predicted performance of the AI model designed in this paper.

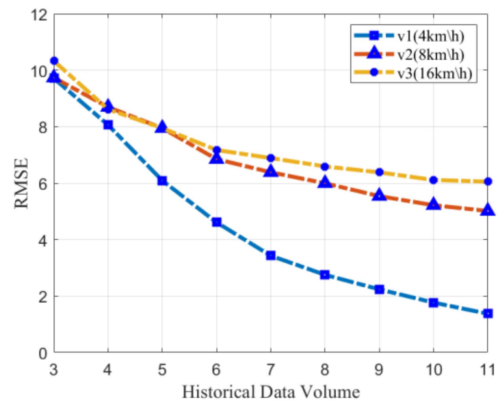

FIGURE 7. RMSE of Tx beam ID between predicted beam and actual best beam with different UE speeds.

The AI model designed for this scheme was validated based on the above parameters. Fig. 6 illustrates the predicted accuracy, represented by the RMSE between the predicted best beam ID and the actual best beam ID. In this experiment, the UE moves at a speed of 4 km/h, changing direction randomly, while maintaining a fixed historical data volume. This demonstrates the excellent predictive performance of the model utilized in this study.

In Fig. 7, the previously mentioned dataset is divided into eleven sub-datasets, which are presented on the horizontal axis. The vertical axis represents the RMSE between the predicted best Tx beam ID and the actual best Tx beam ID, serving as a measure of prediction accuracy. It can be seen that as the duration of data collection increases, all the curves

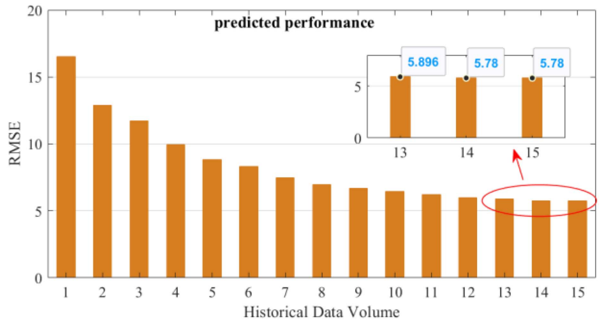

FIGURE 8. RMSE of Tx beam ID between predicted best beam and actual best beam with a UE speed of 12 km/h.

seemingly reach a state of stability, indicating that the accuracy of prediction enters a plateau. Moreover, when the UE speed is elevated, this plateau manifests earlier. Therefore, from these observations, we can conclude that UE speed is a crucial factor influencing the determination of the optimal time window size for collecting input data. It is evident that as the UE speed increases, the size of the time window decreases.

The prediction performance is illustrated in Fig. 8. The UE speed is set to 12 km/h, the dataset is divided into fifteen sub-datasets as shown in horizontal axis. When the historical data volume increases to eight, the RMSE levels off, and it remains nearly stable even as the volume increases to thirteen. In fact, our simulation reveals that the time window size of effective historical data volume in the time domain is longer than the channel coherence time. This is due to several factors. Firstly, when the UE's speed is 12 km/h, the rate of temporal fading is relatively slow, as the movement speed results in minor alterations in signal propagation paths. Secondly, our simulation employs the Scattering MIMO Channel model, where propagation paths follow a line of sight from point to point. This channel model is fundamental, yet we find it adequate to illustrate the inverse relationship between UE's movement speed and the duration of the historical data collection window.

Based on the simulation results, it has been observed that the performance of the AI model does not exhibit indefinite improvement as the amount of historical data increases. To mitigate unnecessary overhead and latency, it is crucial to determine the optimal time window size for collecting historical data initially. The size of the time window can be calculated by considering the UE speed, with a smaller window size allocated as the UE speed increases. Additionally, in order to ensure an ample data volume for the input of the AI model, a judicious selection of continuous historical measurement instances can be made.

V. CONCLUSION

In this paper, we have discussed the progress of AI-based BM in 3GPP based on three aspects: model training, model inference, and model monitoring. Our primary focus is on BM-Case2, where we investigate the factors that impact the determination of the optimal time window size for collecting input data. According to our analysis and simulation results, there is an inverse correlation between the time window size and UE speed. In other words, as the UE speed increases, the effective data collection time window tends to become shorter. Therefore, to avoid unnecessary measurement overhead and latency, it is advisable to determine the optimal time window size based on the UE speed.

Additionally, considering the application conditions of the AI model, continuing and discontinuing historical measurement instances can be flexibly chosen to reduce measurement overhead while still satisfying the required data volume for input.

Overall, our findings contribute to the understanding and improvement of AI-based BM systems in the 3GPP framework. By exploring the impact of UE speed on the optimal time window size for data collection and suggesting strategies to reduce measurement overhead, we aim to enhance the efficiency and effectiveness of AI-based BM.

VI. FUTURE RESEARCH

According to our research findings, the speed of the UE stands out as a crucial factor influencing the duration of the data collection time window. Nevertheless, there are additional factors to consider, including the variety of channel environments (e.g., urban, suburban), UE density, data processing capabilities, and computational resources, among others. These factors warrant further exploration in future studies. Moreover, our simulation in this paper employed a basic scattering MIMO channel model. For the next steps, a more comprehensive channel model will be taken into account.

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