Machine Learning based Beamwidth Adaptation for mmWave Vehicular Communications

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***Abstract*—The incorporation of mmWave technology in vehicular networks has unlocked a realm of possibilities, propelling the advancement of autonomous vehicles, enhancing interconnectedness, and facilitating communication for intelligent transportation systems (ITS). Despite these strides in connectivity, challenges such as high path-loss have arisen, impacting existing beam management procedures. This work aims to address this issue by improving beam management techniques, specifically focusing on enhancing the service time between vehicles and base stations through adaptive mmWave beamwidth adjustments, accomplished using a Contextual Multi-Armed Bandit Algorithm. By leveraging various conditions to train the ML agent of the Contextual Multi-Armed Bandit Algorithm, it seeks to learn about vehicle mobility profiles and optimize the usage of different antenna beamwidth settings to maximize seamless connection time. The extensive simulation results showcase the effectiveness of an adaptive beamwidth for mobility profiles, extending the connection time a vehicle experiences with a base station when compared to the existing strategies.**

***Index Terms*—beamwidth adaptation, mmWave, V2X.**

I. Introduction

The utilization of high-frequency mmWave bands and massive MIMO in 5G New Radio (NR) technology has enabled several desirable features, including increased speeds, low latency, high reliability, and enhanced capacity, making it well-suited for future connected autonomous vehicles [1], [2]. As the vehicular network continues to expand with a growing number of vehicles on the road, 5G NR proves capable of meeting this surge in demand, as it can support 10 to 100 times more users than its predecessor, 4G LTE [3]. Despite its benefits, the deployment of 5G NR in vehicular networks introduces new challenges. Vehicular networks are characterized by a complex and dynamic environment, with rapidly moving vehicles, infrastructure, and obstacles, posing potential issues for data transmission [4]. Challenges such as radio wave reflection, diffraction, and scattering result in multipath propagation and signal degradation, particularly due to the characteristics of mmWave frequencies, which exhibit significant path loss and limited antenna coverage [5]. As vehicular density and mobility increase, relying solely on mmWave base stations might be insufficient to ensure service continuity and wide coverage for multiple vehicles with different mobility profiles. To address these issues and optimize wireless connectivity performance in vehicular networks, the adoption of beam management techniques becomes essential [6].

Beam management encompasses procedures for forming, controlling, and detecting beams, enabling the system to direct highly focused beams towards target users, thereby improving signal quality and minimizing interference [7], [8]. One critical beam management technology for vehicular communication systems is beamforming, which enhances signal quality and increases capacity. However, traditional beamforming with fixed beamwidths may not efficiently cope with the dynamic nature of vehicular networks. To address this, beamwidth adaptation has been proposed as a solution to optimize transmission in vehicular networks [9]. Recent studies have extensively explored the performance of beamwidth adaptation in vehicular networks, emphasizing its potential to cater to the unique challenges posed by vehicular environments [10]–[12].

The work in [10] examines the challenges of using highly directional antennas in mmWave cellular networks, particularly the need for precise beam alignment between a base station (BS) and user equipment (UE). The paper proposes an approach to improve the beam-sweeping process and reduce initial access (IA) delay, which is caused by the necessity to sweep over many directions due to the size of the beam. The proposed solution involves using various beamwidths and requiring sweeping in fewer directions. However, using an adaptive beam could result in a weak received signal and a higher misdetection probability, resulting in increased IA delay. To address these concerns, the paper presents a two-stage solution framework based on a multi-armed bandit (MAB) approach. The results of the experiments show that the proposed algorithm significantly reduces IA delay by over 50% compared to traditional fixed-beamwidth schemes. While the study highlights that using an adaptive beamwidth improves a part of the beam management process, it does not explore how an adaptive beamwidth approach can improve the connection time between a BS and UE.

In [11], the authors aim to enhance the initial access process for mmWave uplink systems, by using the estimated location of UE to reduce the broad full beam sweep for the beam direction toward UEs. The proposed approach optimizes the IA algorithm by estimating the distance and determining an optimal beamwidth that maximizes the connection probability. Compared to the conventional fixed beamwidth (15° in the simulation) procedure, the proposed optimal beamwidth scheme with the new IA and beam adaptation (BA) algorithm achieves up to 1.5 times higher channel gain. By improving the beam sweeping process, this study significantly enhances the beam management process. However, it does not investigate the effects of having a dynamic beamwidth setting.

[12] proposes a beamwidth-aware mmWave scheduling scheme for V2V (Vehicle-to-Vehicle) communications on four lanes highway, supported by sub-6GHz V2X (Vehicle-to-Everything). The proposed scheme enables mmWave transmitters to schedule a mmWave transmission (usually completed sequentially), to several neighbouring vehicles simultaneously by adapting the beamwidth configuration (dividing the beam into several sectors). To achieve this, the study utilizes information from sub-6GHz V2X transmissions to identify the location of neighbouring vehicles and determine the minimum beamwidth for mmWave transmissions. The results demonstrate that this proposal helps increase the amount of mmWave data transmitted to neighbouring vehicles, leading to improved throughput. However, this paper does not consider the effects of antenna gain, coverage area, channel state, scheduling conflicts and interference.

From the literature papers above, it is clear that adapting the beamwidth in vehicular networks can improve the beam management process. However, most research primarily focuses on improving the beam alignment process through several considerations, e.g. location or reduced sweeping. After a thorough search of the available literature, no existing literature directly address to adaptively decide best beamwidth configuration for maximumum seamless connection time by incorporating vehicle mobility context under a realistic vehicular mobility environment. In this paper, the research problem is to identify which "sequence of beams" to use so that we can serve vehicles continuously with the longest connection time. This work investigates the impact of beamwidth on connectivity and coverage performance and proposes a machine learning approach to find best beamwidth configuration for a seamless and robust connection for mobile vehicles. The remainder of the paper is organized as follows: Section II describes the considered scenario and formulation of the beamwidth adaptation problem. In Section III, the proposed beamwidth selection algorithm based on Contextual MAB (C-MAB) [13] is elaborated. The experimental results are explained in Section IV to show the effectiveness of our proposed algorithm. Finally, we draw important conclusions in Section V.

II. Scenario Setup and Problem Formulation

In this study, we focus on a mmWave small cell BS that is deployed to enhance data transfer rates and increase network capacity. The small cell BS considered in our analysis consists of an array of antennas, which are directed towards specific predetermined directions. We assume that the antenna can reconfigure its beamwidth setting to produce different radiation footprints. Fig. 1 illustrates four beamwidth configurations that a small cell BS can operate, each of which has a different coverage. The mmWave small cell BS base is located at a junction in Guildford town center, UK, serving traffic travelling from various directions.

In our scenario, the pathloss model for the 28 GHz mmWave channel is based on [14] which is expressed as

$$PL(d) = PL(d_0) + 10n\log_{10}(d/d_0) + X_g, \quad (1)$$

where d is the distance between the transmitter and receiver antennas in meters, n is the pathloss exponent which is set tp 3.4. The channel fading effect, represented by X_g, is not considered in our analysis. The free space path loss (FSPL) in dB, denoted as $PL(d_0)$, depends on the carrier frequency f_c and is given by the formula $10\log_{10}((4\pi d_0 f_c/c)^2)$, where $d_0 = 1$m. Additionally, there is a height difference of 5m between the small cell BS and the vehicle antennas. Consequently, the distance $\hat{d}$ between the two nodes is related to d by the equation $d = \sqrt{\hat{d}^2 + 5^2}$.

The vehicles involved in the communication are equipped with steerable beam antennas that can track and adjust their orientation towards the BS during the

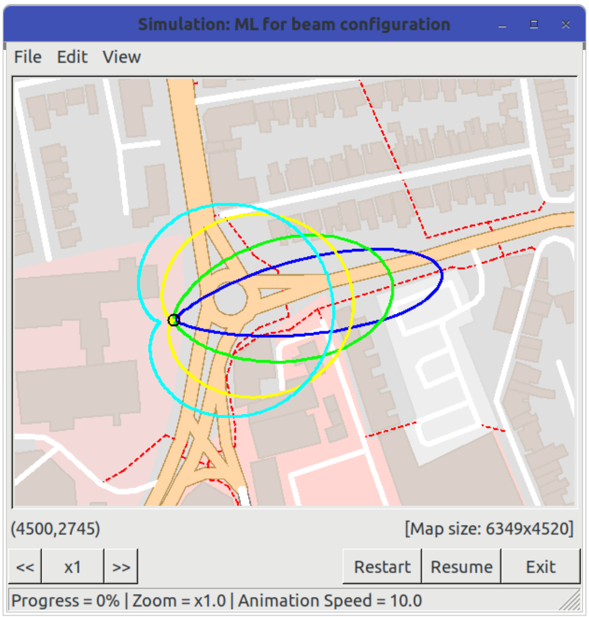

Fig. 1. Illustration of various beam configurations of a mmWave small cell base station.

communication. With this setup, the signal-to-noise ratio (SNR) of a given vehicle being served can be calculated using the following formula

$$SNR = p_0 - PL(d) + G_{tx} + G_{BF}(\Delta\theta) + G_{rx} - N, \tag{2}$$

where p_0 is the transmit power. G_{tx} and G_{rx} are the transmitter and receiver antenna gains, respectively. N is the noise, including thermal noise and the receiver noise figure. We follow the mmWave beamforming model used in [15]. In the study, the beamforming gain G_{BF} of the antenna is calculated based on [16] by

$$G_{BF}(\Delta\theta) = \frac{2\pi}{B_{3dB}} 10^{-0.1\eta\left(\frac{\Delta\theta}{B_{3dB}}\right)^2} \tag{3}$$

where B_{3dB} is the beamwidth of 3dB of the antenna, $\Delta\theta$ is the off-center angle which measures the angle between the beam center direction and its pointing direction to the serving vehicle within its beam sector, and η is a constant carrying a value of 12. Four different beamwidth settings are used in our scenario.

The utilization of mmWave small cells for V2X communication poses a unique challenge, as fast-moving vehicles served by narrow beams leads to short duration of a vehicle's presence within the beam. Consequently, frequent handovers and signaling overheads are resulted. To optimize data transmission between the small cell BS and the vehicles it serves, the radio resource allocation strategy should prioritize serving vehicles that remain within a beam for the longest possible duration. This strategy aims to minimize handovers and signaling overheads, ensuring more stable and efficient communication for V2X scenarios using mmWave small cells [13].

Given the ability of beamwidth reconfiguration, it is possible to identify matching beamwidth setting for some vehicle profiles such that the vehicles can be served with the longest duration while travelling within the small cell BS coverage. In other words, when the small cell BS is ready to serve a vehicle, we aim to find which pair of beam configuration and vehicle to be assigned for service that can maintain the longest connectivity duration. We measure the connectivity duration from the time when the vehicle is assigned a beam, until the vehicle can no longer be served by the small cell BS. During the downlink service, if the vehicle has left the coverage of the existing beam, the BS may reconfigure its beam to continue to serve the vehicle, until none of the configurations can reach the vehicle, then the service is considered ended. The duration of the service is also called vehicle sojourn time.

TABLE I
DOWNLINK COMMUNICATION PARAMETERS USED IN OUR STUDY.

Parameter	**Value**
Center frequency, f_c	28 GHz
Channel bandwidth	50 MHz
Transmit power, p_0	30 dBm
Transmitter antenna gain, G_{tx}	12 dB
Thermal noise	-97.2 dBm
Noise figure	7 dB
SNR threshold	-5 dB
Beamwidth settings, B_{3dB}	17.5, 35, 70, 105 degree

While performing downlink transmission, the BS adaptively adjusts the modulation and coding scheme (MCS) to achieve maximum data rate transmission. The supported maximum data rate for a downlink transmission is given in [17]. Table I summarizes the parameters used in our study for downlink communication from the small cell BS to the serving vehicle.

In order to maximize its service duration for a vehicle, upon departure of a vehicle, the BS immediately selects an available vehicle within its coverage to serve. The BS can unbiasedly select an available vehicle for its next service, or greedily choose a vehicle with the highest SNR. However, based on our earlier work [18], we demonstrated the importance of vehicle profiles for beam-vehicle pairing as vehicle mobility follows local street layout which is predictable. In this work, we further show that vehicle profiles are also critical for reconfigurable antenna when pairing with vehicles. The mobility information used for profiling vehicles shall include vehicle orientation, distance from the BS which can be derived from signal quality, angle of transmission to the vehicle, and the travelling velocity of the vehicle.

III. Proposed Contextual Multi-Armed Bandit Learning Design

We use Contextual MAB (C-MAB) machine learning technique to optimize the selection of vehicles for service. The objective is to select the best combination of beamwidth configuration and vehicle that can yield the longest sojourn time. Thus, the reward for the C-MAB model is the connection duration experienced by a serviced vehicle. Additionally, we consider the mobility information of the vehicle as the context for learning and exploitation.

In our design, the small cell BS can operate using one of the four beamwidth configurations. When the BS is available to perform a downlink transmission, it picks one of the beamwidth configurations to service a vehicle within the beam coverage. The bandwidth of a beam is set to 50 MHz. The BS may be given a bandwidth wider than 50 MHz. In this case, we consider that the BS can serve multiple vehicles independently by partitioning the bandwidth into multiple 50 MHz bands. Without loss of generality, we focus on a particular 50 MHz frequency band.

Our C-MAB operates in either exploration or exploitation modes. We use explore-first strategy with sufficient exploration for the learning. During the exploration, the BS randomly picks a beamwidth setting and a vehicle within the beam coverage to perform a downlink transmission. The mobility profile of the picked vehicle is also captured. With full buffer assumption, the BS continues to transmit the data using appropriate MCS to achieve supported maximum data rate transmission as derived in [17]. If the vehicle has left the beam coverage, the BS attempts to reconnect the vehicle immediately using a different beamwidth setting. If none of the beamwidth settings can reach the vehicle, the vehicle is said to have left the BS, and the downlink service is considered ended. The duration of the service is measured and used as the reward associated with the mobility profile of the served vehicle. The ML agent continues to learn the reward of various mobility profiles during the exploration.

Once the exploration phase is completed, the ML agent switches to exploitation. In the exploitation phase, whenever the BS is ready to perform the next service, it picks the vehicle that can yield the highest reward among other vehicles. Precisely, the ML agent ranks the learned profiles based on their rewards, and it searches for an available vehicle whose profile has the highest reward in the ranked profiles. The available vehicle will then be served by the beamwidth setting based on the ranked profile accordingly. If none of the available vehicles have a profile matching that in the ranked profiles, a random selection of an available vehicle is performed. In this case, the ML agent will learn this unseen profile.

We use mobility information as the context of C-MAB for profiling vehicles. The mobility information consists of vehicle orientation, signal strength for the distance from the BS, angle of transmission, and travelling velocities of the vehicle. The following elaborates our design of vehicle mobility profiling:

- Vehicular Orientation: four directions are considered, which are 'North', 'East', 'South' and 'West'.
- Vehicular Speed: the vehicle is considered 'Slow' if the speed is below 25 km/h. Otherwise, it is considered 'Fast'.
- Signal Strength: it is measured by Reference Signal Received Power (RSRP) in dBm. Four levels are used, which are 'Excellent' if $RSRP > -70$, 'Good' if $RSRP \in [-70, -80)$, 'Fair' if $RSRP \in [-80, -90)$, or 'Poor' is $RSRP \leq -90$.
- Angle of Transmission: it measures the transmission angle from the BS to the vehicle relative to the BS pointing direction. Three categories are used. If the vehicle is within ± 45 of the BS point direction, it is considered as 'Center'. Otherwise, if the vehicle is more than ± 45 from the BS point direction residing on the left (resp. right) side of the BS pointing direction, it is said to be on the 'Left' (resp. 'Right').

Given the above vehicle mobility profiling scheme, we can derive 96 unique profiles to describe the vehicle mobility. The objective of ML agent is to learn the reward of each profile when served by a beam with a specific beamwidth setting. As the context space is relatively small, we use explore-first as our exploration-exploitation strategy. The aim during the exploration phase is to establish as much knowledge as possible about the profiles and their corresponding reward. During the exploitation, if the learning is insufficient where the ML agent cannot identify a vehicle to serve, it will perform exploration to fill its learning gap. The online learning feature of C-MAB can continue to acquire new knowledge or reinforce its learning as it exploit the learned knowledge.

IV. Result Discussion

In this section, we present the simulation results and show the effectiveness of our beanwidth adaptation using ML technique. We utilize our custom-developed Python Mobility Simulation Platform (PyMoSim) to conduct the simulations and obtain the results. The simulation involves a large number of vehicles of over a hundred continuously moving on the map. We simulate 6 hours of operation, during which the BS undergoes a two-phase operation. In the first 2 hours, the BS performs full exploration for learning purposes. Subsequently, it switches to full exploitation. By implementing the Explore-First strategy in this manner, we can concentrate on studying the effectiveness of the learning acquired during the initial exploration phase. This approach allows us to focus on the learning phase impact on the performance and efficiency of C-MAB models, as exploration is no longer considered after the learning phase is completed.

To show the performance benefit of considering vehicle mobility profiles for beamwidth setting, we compare the C-MAB solution with random selection and BestSNR strategy. The Best SNR strategy is a commonly used technique in BSs to greedily serve users. Fig. 2 presents the average service duration of vehicles over the simulation time. As can be seen, during the exploration phase, all methods produce similar results where the average service duration is around 17 seconds. During this phase, C-MAB uses random selection to acquire knowledge, and hence the performance is similar to that of the random selection. Interestingly, the BestSNR strategy also produces similar results. During exploitation phase, the ML agent utilizes its learned knowledge to select the vehicle that can yield the highest reward. As a result, the service duration of C-MAB jumps to above 25 seconds on average which is more than 40% improvement, and it records peak service duration of over 30 seconds.

In Fig. 3, we further compare the average downlink transmission data rate between the random selection, BestSNR strategy and our proposed C-MAB solution. We see that BestSNR yields slightly higher data rate than others due to its design of selecting the vehicle with the highest SNR for service, the C-MAB solution gives comparative data rate performance during the exploitation. The results suggest that while C-MAB attempts to maximize the service duration, its decision does not sacrifice the data rate performance. The BestSNR strategy often picks vehicles near the BS to begin its service, while C-MAB picks vehicles near the beam-edge. Although the vehicles picked by C-MAB begins from the beam-edge, they often travel towards the BS which allows them to enjoy high data rate transmission while they travel near the BS. Consequently, C-MAB solution not only produces the longest service duration, the data rate performance is comparable to that of the BestSNR strategy.

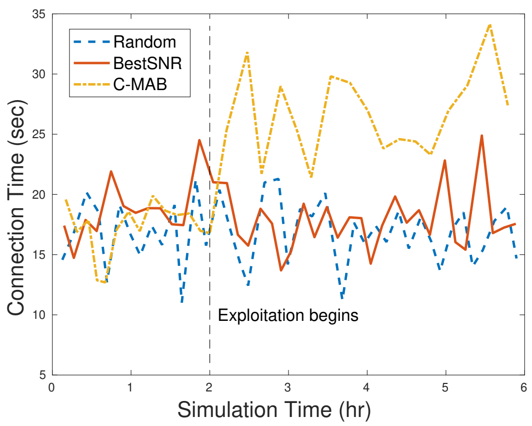

Fig. 2. Service duration versus simulation time for random selection, BestSNR strategy and C-MAB solution.

V. Conclusion

In this paper, we considered a mmWave small cell BS with adaptive beamwidth settings. We developed a machine learning technique to adaptively adjust beamwidth settings to provide the longest service duration to vehicles. We applied Contextual Multi-Armed Bandit (C-MAB) machine learning technique

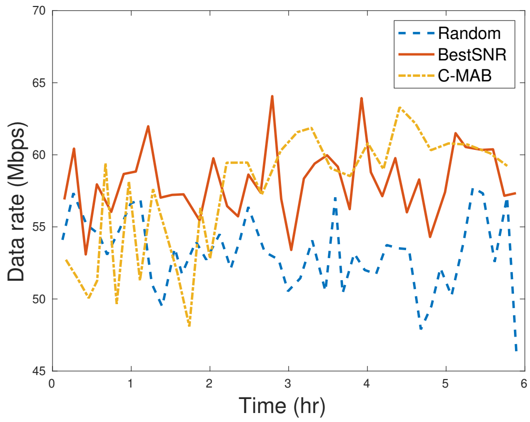

Fig. 3. Data rate performance comparison between random selection, BestSNR strategy and C-MAB solution.

to learn how vehicle mobility information influence the service duration performance under various beamwidth settings and utilize the learned knowledge to identify the available vehicle that can potentially offer the longest service duration with the best beamwidth setting. In our design, we profiled vehicle mobility using various information including the vehicle travelling direction and speed, received signal strength, angle of transmission from the BS to the vehicle. Our profiling produced 96 unique mobility profiles which are relative small for efficient learning. We demonstrated that with the profiling approach in C-MAB, our ML solution achieves over 40% improvement in the service duration and we also showed that the average data rate during the service is comparable to that of the BestSNR which aims to achieve the highest data rate transmission.

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