Millimeter-Wave Vehicle-to-Infrastructure Communications for Autonomous Vehicles: Location-Aided Beam Forecasting in 6G

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***Abstract*—The rise of autonomous vehicles has generated substantial interest due to their potential to transform transportation, enhance safety, and reduce traffic congestion in urban areas. This research investigates strategies to facilitate communication among various elements in driving environments, such as vehicles, pedestrians, and emergency responders, primarily focusing on vehicle-to-infrastructure (V2I) communication. Furthermore, advancements in wireless technology, including 6G and millimetre waves, offer improved connectivity but face challenges in signal propagation. The study emphasizes the importance of beamforming as a solution, exploring alternative, resource-efficient methods to predict optimal signal directions using user positions. Positive simulation results suggest real-world applicability, and the study addresses critical questions about utilizing future positions and their impact on overhead complexity. This research provides valuable insights into position-based approaches for enhancing wireless communication in autonomous driving scenarios.**

***Index Terms*—Autonomous vehicles, overhead complexity, training overhead, beam prediction, 6G.**

I. Introduction

Having the potential to transform transportation advances in artificial intelligence, autonomous vehicles have attracted remarkable interest from governments, industries, and the public [1]. The spread of autonomous vehicles gives assurance for decreasing road accidents and relieving traffic congestion, thereby improving transportability in densely populated urban areas [2]. However, in everyday driving environments, other elements must be considered: vehicles, pedestrians, emergency vehicles, motorbikes, and cyclists. Autonomous vehicles communicate to vulnerable road users as a substitution for, for example, driver-pedestrian communication, which can lead to increased safety [3]. With this in mind, a goal is to design and implement a cooperative system based on communications that promise information exchange among these elements in a close environment.

Different approaches for solving this problem have been proposed. Recent advances in 3GPP release 16 have started a new era of road connectivity and safety by introducing the 5G NR-V2X standard, which offers ultra-low latency and high reliability, enabling faster communication between vehicles, infrastructure, and pedestrians [4]. Also, the US Department of Transportation proposes, under the IntelliDrive initiative, the development of safety and mobility applications to identify possible crash scenarios and give warnings to drivers through opportune visuals or aural warnings. The communication standards defined for Wireless Access in Vehicular Environments (WAVE) give basis to these applications: IEEE 1609 and IEEE 802.11p WAVE systems used for dedicated short-range communication (DSRC) consist of three elements, i.e., the roadside unit, the onboard unit and the service channels which are designed to be installed on traffic lights, signals, and other road elements, mounted on the vehicles to guarantee connectivity and to allow bidirectional V2I connectivity simultaneously [5]. In V2I communication, the precise knowledge of where to send signals from a base station is of utmost importance because it plays a vital role in enabling communication between vehicles and the surrounding infrastructure. The base station is a central hub for transmitting and receiving data between vehicles and these infrastructure elements. Knowing where to direct the signals is critical to ensure efficient and effective communication. If signals are sent to the wrong location or time, it can lead to delays, miscommunication, and even safety risks on the road. Another fundamental challenge in V2I communication is optimizing the wireless link between vehicles and infrastructure, considering the dynamic nature of vehicular networks. Beamforming, a sophisticated technique rooted in wireless communication, offers an innovative approach to address these challenges. It involves shaping and directing radio frequency signals in a focused manner toward a specific direction, resulting in improved signal strength, reduced interference, and enhanced spectral efficiency.

Every new generation of wireless communication assures a new path of associating and conveying and more ability to give better production in this repeatedly substituting era of wireless communication. Advancing 6G wireless technology is not divergent and unlocks new possibilities [6]. In the current state of the art, the idea of millimetre waves has been getting a lot of recognition. It is essential for 6G networks and could lead to a novel epoch of upgraded connectivity and revolution [7]. However, there is a new challenge of being unable to travel through obstacles like buildings or trees very well, and the atmosphere can absorb them, making it challenging to keep fast and dependable connections [8]. The routine way of using omnipresent antennas, which can send signals in every direction, does not work at its best in these scenarios. Beamforming offers a vital solution to this problem [9]. Previously, artificial intelligence techniques, like neural networks, were the preferred choice for predicting the best possible direction for wireless signals in 5G and approaching 6G technologies [10]. These AI models performed best at figuring out where to point the wireless beams by training on lots of data and adapting to different situations. However, recently, there has been a growing interest in finding faster and more efficient ways to make these predictions. Despite being powerful, it needs a lot of computer power and data, which is difficult to always have available, especially on small devices at the network's edge [11]. So, our research focuses on alternative methods that are less demanding but still work well for predicting where to send wireless signals. It is beneficial for places where resources are limited.

There are ample studies in existing research that have explored how we can make wireless communication systems work better by using user positions. In one study [12], researchers have used support vector machines to help with how wireless signals are pointed in a computer simulation with many users and cells. This study assumed everyone's positions were known and focused on making better decisions without artificial intelligence. Another study [13] used deep neural networks to improve how wireless signals are directed. Although it is essential to note that they have used made-up positions and orientation data for the wireless devices for simplicity, this indicates we can improvise without artificial intelligence. Another study [14] on making wireless signals work better using a lookup table. Yet, this still depends on the knowledge of positions with the help of the global positioning system. In another study [15], different methods relying on machine learning to improve wireless communication consider errors when knowing users' positions. Though it is essential to know that they have added some random errors to simulate problems with the global positioning system, this may not be the ideal reflection of real-life scenarios because it does not consider how errors in knowing positions are related.

The positive results from simulations open the possibility of achieving similar results in the real world using standard global positioning system devices and millimeter-wave communications systems. Yet, few studies have looked into real-world scenarios when we consider using position information to estimate the direction of signals in future simulations. With this goal in mind, this study makes the following contributions:

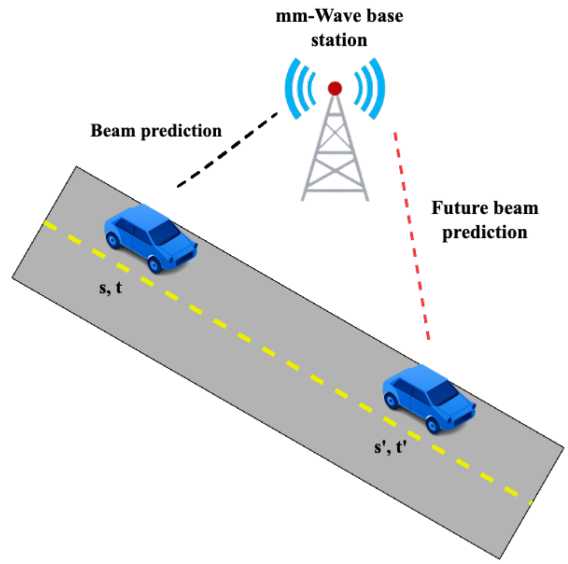

Fig. 1. Network model for 3GPP release 16 V2I.

- Our approach outperforms the baseline model in predicting current beam accuracy. We identify various factors influencing accuracy, including scenario complexity, data quality, model selection, feature relevance, data sample size, and more.
- Designed to subside the quantity of beams necessitating training, our approach pioneers a novel methodology for achieving overhead savings. This approach helps reducing the computational requirements.
- Our approach uses GPS devices and location tools for real-time prediction of vehicle positions which comes up with to the reliability of mm-Wave communication in a wireless network. We optimize beam angles, minimizing issues and ensuring fast, stable connections by anticipating future locations.

The data from 60 GHz channel measurements and global positioning system positions address specific questions. Rest of the paper is divided as follows: we define problems in Section II. It also makes us understand how the system works. Section III details how we collected real-world data and what steps we followed to prepare this data for analysis. Section IV provides the method we follow for future beam predictions, and Section V provides the results and discussion with the conclusion drawn in Section VI followed by acknowledgement in Section VII.

II. System Model Including Problem Formulation

A. System Model

As one can see in Fig. 1, We are examining a system in which a base station equipped with M antennas communicates with user equipment having a single antenna. The communication is facilitated by one of the N available beam forming vectors denoted as $\mathbf{f}_n$, belonging to a predefined codebook F represented as $F = \{\mathbf{f}_n\}_{n=1}^{N}$ If we denote the transmitted complex symbol by the BS using the chosen beamformer $\mathbf{f}_n$ as 'x', which is the symbol received by the UE in the downlink communication is given by the following expression:

$$y = \mathbf{h}^T \mathbf{f}_n x + \mathbf{m}, \tag{1}$$

Where $\mathbf{h} \in \mathbb{C}^{M\times 1}$ consists of the amplitude and phase transformations that occur between each BS antenna and the UE antenna, and $\mathbf{m} \sim \mathcal{N}_{\mathbb{C}}(0, \sigma^2)$ represents complex normally distributed noise.

B. Problem Formulation

BS selects the beam former that results in the highest received power $P = E[|y|^2]$. This is how optimal beam selection occurs. Here, we have selected receive power as a performance metric. The ideal beam former f^* can be obtained by using:

$$\mathbf{f}^* = \underset{\mathbf{f}\in F}{\operatorname{argmax}}\, |\mathbf{h}^T \mathbf{f}|^2. \tag{2}$$

We target predicting the optimal beam based solely on the real-time position information of the UE instead of relying on the explicit channel knowledge, i.e., the knowledge of $\mathbf{h}$, which is challenging to acquire.

III. DATASET DESCRIPTION WITH MEASUREMENTS

The data used in this research makes up a portion of the DeepSense dataset [9]. The dataset is an extensive real-world data collection carefully organized by the Wireless Intelligence Lab. It consists of different data sources, including global positioning system locations, camera images, RADAR, LIDAR, and power measurements from beam training. They are all integrated into each individual data point. For the sake of this research, we emphasized the calibrated global positioning system positions, time stamps, and power data taken from DeepSense scenarios 1 to 9. We emphasized the procedures for acquiring the dataset and elaborated on the pre-processing we applied.

A. Data Acquisition

The DeepSense dataset consists of data gathered at different locations across the Arizona State University campus during both day and night. The data was collected using user equipment placed inside a moving car equipped with a global positioning system and a millimeter-wave transmitter working at 60 GHz. The base station is stationary and equipped with a mm-wave receiver and a uniform square array of 64 antenna elements. The car passes in front of the base station from different directions in the experiments. The base station performs a sweeping operation across a codebook denoted as F and samples the received powers for every 64 possible beams approximately ten times a second.

B. Data Pre-processing

We follow the common practice of normalization while training machine learning models. We have used the min-max normalization method, focusing on normalizing the latitude and longitude coordinates of user equipment. After concluding that a big difference was not observed in how well our models performed after splitting in different ways, we divided the data for each scenario into percentage ratio of 50:25:25 for training, validation and testing.

IV. FORECASTED POSITION-AIDED FUTURE BEAM PREDICTION

Millimeter-wave communication relies on concrete beams, and it is essential to have a clear line of sight. That is why we are using the positions of devices in our study. After learning a proper mapping between positions and ideal beams, we can predict the best beams for communication. This map can be constructed using past observations of where devices were located and which beam worked the best. This works well at the infrastructure sites. In this section, we will explain our approach by looking at it through machine learning. We will also clarify why we have opted for this specific method.

$\mathbf{f}^*$ has been approximated through a prediction function $f_\Theta(g)$ parameterized by a set Θ that represents the parameters of the model. A dataset $D = \{(g_k, \mathbf{f}_k^*) : k = 1,..,K\}$, which is composed of K labeled training samples, helps learn the parameters Θ. Each sample has its ground truth optimal beamforming vector $\mathbf{f}_k^* \in F$ and the input location g_k. For that reason, for a given position g, we have $\hat{\mathbf{f}} = f_\Theta(g)$. The beamformer with the highest probability is chosen. Our algorithm estimates a probability distribution $P \in \{p_1, ...p_N\}$, where $p_n = \mathbf{P}(\mathbf{f}_n = \mathbf{f}^*)$. $\mathbf{f}$ is as follows:

$$\hat{\mathbf{f}} = \mathbf{f}_{\hat{n}}, \;\; \hat{n} = \underset{n\in\{1,\ldots,N\}}{\operatorname{argmax}}\; p_n. \tag{3}$$

A. Beam Prediction

Beam prediction helps select the most likely sequence of outputs from a set of possibilities. In this context, Long Short-Term Memory (LSTM) networks have been employed for beam prediction tasks due to their ability to capture sequential and long-range dependencies. Similarly, Random Forest, a robust ensemble learning algorithm, has also been explored for beam prediction tasks, offering the advantage of handling high-dimensional feature spaces. Two approaches, LSTM and Random Forest, have been applied to beam prediction to improve accuracy and efficiency, and their comparative analysis can provide valuable insights into their respective strengths and weaknesses in different application domains.

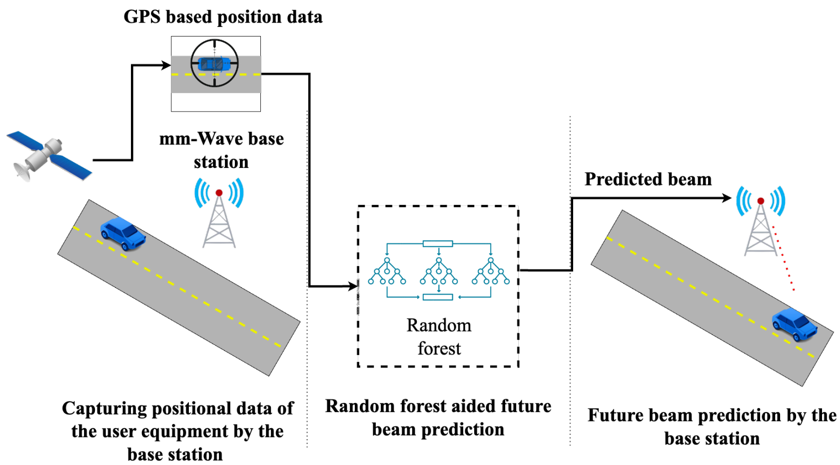

Fig. 2. Proposed block diagram for future beam prediction.

B. *Key Idea: Why future beam prediction?*

The essential part of our approach is predicting where the vehicles will be after a specific time. We take into account that vehicles in a wireless network are always moving. For this, we use global positioning system devices and similar location tools to create reliable predictions about the future positions of the vehicles in a network. This system can adjust in real-time as vehicles are to help us forecast how beams should be. We are trying to determine the optimal angles by anticipating where vehicles will be in the network. This helps make mm-Wave communication more trustworthy. Predicting the vehicles is essential for finding the best direction for the future beam. It ends up reducing problems and keeping the connections fast.

C. *Proposed System Operations*

1) Preparing Time Dataframe: A time data frame has been created to predict the future positions of a vehicle. To obtain timestamp data, a CSV file containing information about the vehicle's movement over time is useful. This data is then organized in a structured format with a timestamp as one column using Python. Analyzing and manipulating data helps make predictions about the vehicle's future positions. This data explores patterns and trends in the vehicle movement data and improvises the model.

2) Predicting Future Positions: Forecasting future positions based on instantaneous Velocity is a primary concept with wide-ranging applications. The method is based on the relationship between an object's velocity and position over time. We can estimate where the object will be in the future after knowing the object's current Velocity and its initial positions. The estimation can be instrumental in scenarios where tracking or forecasting an object's movement is necessary. The following variables are essential for the foundational mathematical formula to predict an object's position: Position (s): This is the location of the object in space, typically in three-dimensional coordinates (x, y, z). Instantaneous Velocity (v): Instantaneous velocity represents the object's speed at a given moment. It includes information about both the object's speed and its direction. You must know how the Velocity changes with time to predict future positions. Time (t): The time elapsed since you last measured the object's position. The formula to calculate the predicted position (s') of an object at a future time (t') based on its instantaneous Velocity is as follows:

$$s' = \frac{s}{t} \cdot (t' - t) \tag{4}$$

In this scenario, we have two distinct time points: t, which represents the initial moment, and t', which signifies a future time point. Additionally, we are working with two corresponding positions, denoted as s for the initial position and s' for the anticipated or predicted position at time t'. This distinction in time and position allows us to track changes and predict where an object or entity will be in the future based on its initial location at time t. It's a fundamental concept in various fields like physics, mathematics, and predictive modelling, aiding in our understanding of how objects or systems evolve over time.

3) Predicting Beam Index for the Forecasted Positions: Artificial intelligence models can potentially change beam prediction processes, offering many advantages over classic approaches. This model performs best at recognizing intrinsic patterns in the data, providing more precise forecasting. They are good at generalizing in different scenarios as well as adaptable. This model is vital for beam prediction tasks as it efficiently processes large volumes of complex data.

4) Random Forest: Random forest is one of the most powerful supervised machine learning algorithms today, and its fundamental aspect is the decision tree algorithm. Random forests excel at capturing intricate patterns within the data. Combining the outputs of multiple constructed decision trees mitigates the risk of overfitting the data. Random forests are

Algorithm 1 Psuedo code for Random Forest Algorithm

procedure RANDOMFOREST($\mathcal{D}$, N, M, m, f)
  $\mathcal{F} \leftarrow []$ {Initialize empty list of decision trees}
  for $i \leftarrow 1$ to N **do** {Build N trees}
    $\mathcal{D}' \leftarrow$ BOOTSTRAPSAMPLE($\mathcal{D}$) {Create a bootstrap sample}
    $T \leftarrow$ BUILDDECISIONTREE($\mathcal{D}'$, M, m, f) {Build a decision tree}
    $\mathcal{F} \leftarrow \mathcal{F} + [T]$ {Add the tree to the forest}
  end for
  return $\mathcal{F}$ {Return the Random Forest}
end procedure

also adept at handling noisy data and missing values without losing performance. Several more compelling reasons for their effectiveness in beam prediction, like having a built-in mechanism for feature selection and automatically identifying the most relevant input variables, help enhance prediction accuracy and reduce computational overhead. It enhances generalization, which makes them suitable for a wide range of beam prediction scenarios. Random forests are also less sensitive to input data scaling, which makes them well-suited for datasets with different measurement scales. Finally, their interpretability allows researchers to gain insights into the factors influencing beam indexes, facilitating a better understanding of the underlying physical processes. Collectively, these features make random forests a highly effective and versatile method for beam prediction in various research contexts.

V. RESULTS

The findings of our two main parts are shown in this result section. First, we are looking at performance metrics to assess how well our approach works. We used accuracy to evaluate the effectiveness of our approach. Secondly, we assess the number of overhead savings achieved through this method. We calculated how much resources, such as time, helped us save with this approach. These results provide valuable insights into the results.

A. Performance metrics

In Fig. 3, we compared our model's accuracy with the baseline for current beam prediction [15], demonstrating our model's improvement. Fig. 4 presents future accuracy across nine scenarios (Scenarios 1 to 9). Low accuracy in some systems is influenced by complexity, data quality, model suitability, feature selection, data sample size, overfitting, external factors, and data imbalance. Improving accuracy involves technical analysis, model refinement, scenario-specific adjustments, data quality enhancement, and careful performance metric consideration.

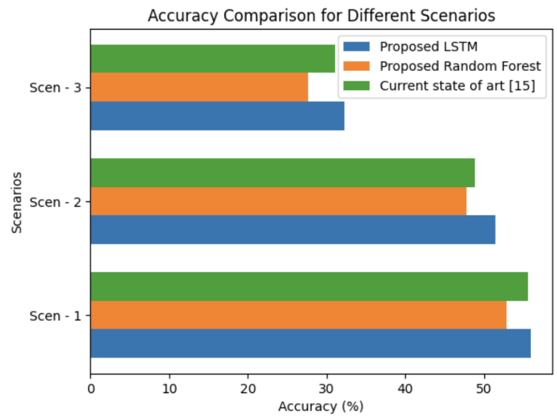

Fig. 3. Comparative analysis of hitting accuracy with the baseline of current beams compared to the ground truth across different scenarios.

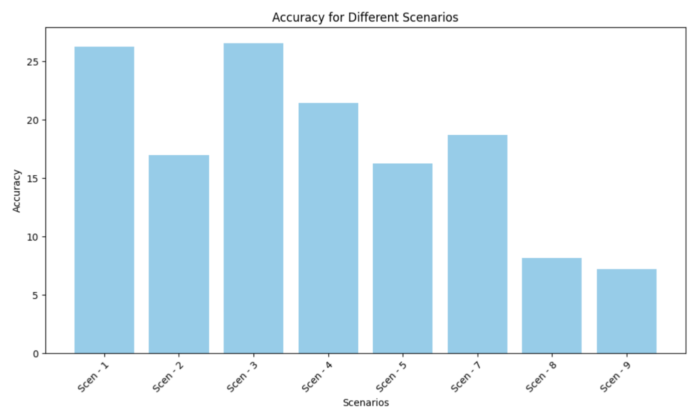

Fig. 4. Hitting accuracy of future beams compared to the ground truth across different scenarios.

B. Reduction in Overhead due to GPS

Suppose we define overhead savings as reducing the number of beams that need to be trained. In that case, we can ensure that the level of overhead depends only on the reliability (or the probability that our system works correctly) we desire for our machine-learning task. Reliability represents our confidence in a specific group of beams containing the best option. The higher our confidence, the larger the group of beams we need, which reduces our overhead savings.

Let's say all 64 beams need training for our system to find the best candidate. Then, with a reliability of $\alpha_{OH}^{(90)}$ at least 90%, denoted as (90), we can calculate our overhead savings as follows:

$$\alpha_{OH}^{(90)} = 1 - \frac{b^{(90)}}{M} \tag{5}$$

Where $b^{(90)}$ is the minimum number of beams needed, on average, so that their probabilities add up to more than 90%, and M is the codebook size. Fig. 5 presents the overhead savings across different scenarios for reliability values when

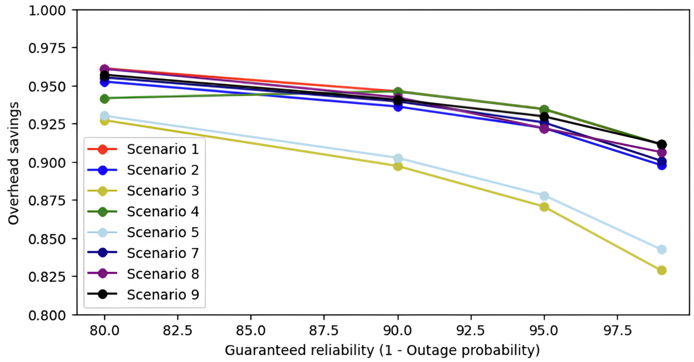

Fig. 5. Overhead savings as a function of outage probability across different scenarios.

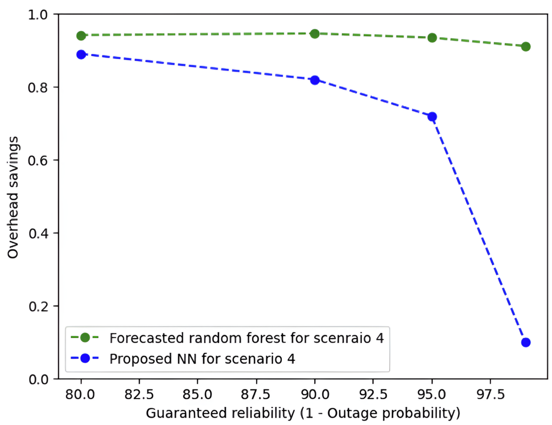

Fig. 6. Comparative analysis of overhead savings as a function of outage probability with the baseline in scenario 4.

M = 64. For instance, with a 90% reliability (a 10% chance of something going wrong), our approach can save between 90% and 96% of training overhead, depending on the specific scenario. For a 99% reliability, our method reduces training overhead by an average of 86%. Fig. 6 compares the baseline model overhead savings with the proposed forecasted random forest [15]. It is observed that the forecasted random forest performs significantly well in comparison to the baseline model, with around 99 % reliability.

VI. Conclusion

In conclusion, this research has explored methods to enhance wireless communication systems, focusing on leveraging user positions in the context of millimeter-wave and 6G wireless technology. Using future positions for predicting future beams shows promise in simulation studies, offering exciting prospects for real-world wireless communication improvement. The study also delved into the impact of incorporating position data on complexity, shedding light on practical implementation considerations. This paper demonstrates improvements over baseline models in achieving reliability. By using data from 60 GHz channel measurements and GPS positions, this research provides valuable insights into the feasibility of these approaches, offering practical solutions for more efficient wireless communication. However, further real-world exploration is necessary to fully understand the practical implications of using position information for beam predictions.

VII. Acknowledgement

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References

[1] L. Chen et al., "Milestones in autonomous driving and intelligent vehicles: Survey of surveys", IEEE Trans. Intell. Veh., vol. 8, no. 2, pp. 1046-1056, Feb. 2023.

[2] W. Wang, L. Wang, C. Zhang, C. Liu and L. Sun, "Social interactions for autonomous driving: A review and perspectives", Found. Trends Robot., vol. 10, no. 3-4, pp. 198-376, 2022.

[3] Jun Wang, Li Zhang, Yanjun Huang, Jian Zhao, "Safety of Autonomous Vehicles", Journal of Advanced Transportation, vol. 2020, Article ID 8867757, 13 pages, 2020. https://doi.org/10.1155/2020/8867757

[4] A. Kousaridas, D. Medina, S. Ayaz and C. Zhou, "Recent advances in 3GPP networks for vehicular communications," 2017 IEEE Conference on Standards for Communications and Networking (CSCN), Helsinki, Finland, 2017, pp. 91-97, doi: 10.1109/CSCN.2017.8088604.

[5] R. Uzcategui and G. Acosta-Marum, "Wave: A tutorial", IEEE Commun. Mag., vol. 47, no. 5, pp. 126-133, May 2009.

[6] W. Jiang, B. Han, M. A. Habibi and H. D. Schotten, "The Road Towards 6G: A Comprehensive Survey," in IEEE Open Journal of the Communications Society, vol. 2, pp. 334-366, 2021, doi: 10.1109/OJ-COMS.2021.3057679.

[7] W. Hong et al., "The Role of Millimeter-Wave Technologies in 5G/6G Wireless Communications," in IEEE Journal of Microwaves, vol. 1, no. 1, pp. 101-122, Jan. 2021, doi: 10.1109/JMW.2020.3035541.

[8] M. Z. Chowdhury, M. Shahjalal, S. Ahmed and Y. M. Jang, "6G Wireless Communication Systems: Applications, Requirements, Technologies, Challenges, and Research Directions," in IEEE Open Journal of the Communications Society, vol. 1, pp. 957-975, 2020, doi: 10.1109/OJ-COMS.2020.3010270.

[9] W. Jiang and H. D. Schotten, "Initial Beamforming for Millimeter-Wave and Terahertz Communications in 6G Mobile Systems," 2022 IEEE Wireless Communications and Networking Conference (WCNC), Austin, TX, USA, 2022, pp. 2613-2618, doi: 10.1109/WCNC51071.2022.9771738.

[10] Bai, C., Nguyen, H., Asteris, P. G., Nguyen-Thoi, T., Zhou, J. (2020). A refreshing view of soft computing models for predicting the deflection of reinforced concrete beams. Applied Soft Computing, 97, 106831.

[11] Allen, G. (2020). Understanding AI technology. Joint Artificial Intelligence Center (JAIC) The Pentagon United States.

[12] G. Eason, B. Noble, and I. N. Sneddon, "On certain integrals of Lipschitz-Hankel type involving products of Bessel functions," Phil. Trans. Roy. Soc. London, vol. A247, pp. 529–551, April 1955.

[13] J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68–73.

[14] I. S. Jacobs and C. P. Bean, "Fine particles, thin films and exchange anisotropy," in Magnetism, vol. III, G. T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp. 271–350.

[15] Morais, J., Behboodi, A., Pezeshki, H., Alkhateeb, A. (2022b). Position aided beam prediction in the real world: How useful GPS locations actually are? arXiv (Cornell University). https://doi.org/10.48550/arxiv.2205.09054