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ENHANCING BEAMFORMING AND INTELLIGENT BEAM SELECTION FOR MILLIMETER-WAVE COMMUNICATION USING ADAPTIVE BEAMFORMING TECHNIQUES

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ABSTRACT

In the rapidly evolving landscape of mobile telecommunication, the optimization of beamforming strategies stands as a critical element for ensuring the efficiency and robustness of wireless communication networks. This research endeavors to contribute to the advancement of beamforming in mobile networks by delving into the analysis of beamforming feedback datasets. The primary objective is to employ machine learning techniques, with a focus on Support Vector Machines (SVM), to categorize beams into distinct strength categories. Subsequently, an adaptive beamforming algorithm is applied to identify and select the optimal line-of-sight (LOS) beam, thereby enhancing the overall performance of 5G beamforming. The classification of beams using SVM with a beamforming feedback dataset serves as a pivotal technique in optimizing the 5G beamforming process. The ultimate goal is to dynamically adjust the direction of beams based on the strength of received signals, thereby augmenting communication quality and efficiency. Parameters such as interference level, bit error rate, and latency are crucial in evaluating the performance and reliability of communication systems. This research not only investigates the intricacies of beamforming feedback datasets but also proposes a novel approach to adaptively optimize beam directionality in 5G networks. By integrating SVM-based beam classification and adaptive algorithms, this work aims to contribute to the evolution of mobile telecommunication, enhancing the communication quality and reliability of 5G networks.

Keywords: *Beamforming, Mobile Networks, Machine Learning, Support Vector Machines (SVM), Beamforming Feedback, Line-of-Sight.*

1. INTRODUCTION

In the rapidly evolving landscape of mobile telecommunication, the demand for faster data rates, improved spectral efficiency, and seamless connectivity has become more pronounced than ever before. As the world becomes increasingly interconnected, the need for innovative technologies that can address the challenges of network congestion, signal interference, and limited bandwidth has become a critical focal point for researchers and industry professionals alike. Among the transformative technologies that have emerged to meet these demands, beamforming stands out as a promising solution that holds the potential to redefine the way we experience mobile communication.

Beamforming, a technique that leverages the principles of antenna array signal processing, allows for the precise directional transmission and reception of signals. This capability opens up new avenues for enhancing the performance of mobile communication systems by mitigating interference, improving signal quality, and maximizing the utilization of available spectrum. This thesis delves into the intricacies of beamforming and its application in mobile telecommunication, exploring the theoretical foundations, technological advancements, and practical implications that shape its role in shaping the future of wireless communication.

The overarching goal of this research is to provide a comprehensive understanding of beamforming in the context of mobile telecommunication, shedding light on its potential to revolutionize the way we design, deploy, and experience wireless networks. Through a thorough examination of the current state-of-the-art techniques, challenges, and future prospects, this thesis aims to contribute valuable insights to the academic and industrial communities working towards the advancement of mobile communication systems. As we embark on this journey through the realm of beamforming, we anticipate unraveling the key principles that underpin its effectiveness and exploring the innovative applications that promise to usher in a new era of connectivity and communication.

1.1 Advantages

- Enhanced Data Rates: Beamforming allows for the precise focusing of radio waves, enabling higher data rates for users. By concentrating the signal energy in the direction of the user or device, beamforming minimizes interference and increases the signal strength, leading to faster and more reliable data transmission.
- Increased Capacity: Beamforming enables 5G networks to serve multiple users simultaneously in the same frequency band. This multi-user MIMO (Multiple-Input, Multiple-Output) technology enhances network capacity, ensuring that more devices can connect and use the network without sacrificing performance.
- Improved Coverage and Range: 5G beamforming can extend coverage and reach in challenging environments. By directing signals where they are needed, it can overcome obstacles, such as buildings or vegetation, and reach users at longer distances, thus expanding the network's effective range.
- Lower Latency: Reducing latency is a crucial aspect of 5G, and beamforming plays a role in achieving this goal. By optimizing signal transmission paths, beamforming minimizes signal travel time, resulting in lower latency connections, which are essential for applications like autonomous vehicles and augmented reality.
- Energy Efficiency: Beamforming enhances energy efficiency in 5G networks. By transmitting signals precisely to the intended recipients, it reduces unnecessary radiation in all directions, leading to less power consumption and longer device battery life.
- Improved Quality of Service: With beamforming, 5G networks can offer a more consistent and reliable quality of service. The technology minimizes signal interference and fluctuations, ensuring a stable connection for users, even in densely populated or high-mobility environments.
- Network Customization: Beamforming provides flexibility in shaping the coverage area and directing resources where they are needed. Network operators can adapt beamforming parameters to cater to specific scenarios, such as stadium events, urban deployments, or rural areas, allowing for network customization based on demand.
- Interference Mitigation: 5G beamforming can actively reduce interference from other users and neighboring cells. By steering beams away from sources of interference, it enhances the overall network performance and reliability.
- Spectrum Efficiency: By concentrating signal energy in specific directions, beamforming enables more efficient use of the available spectrum. This is essential for optimizing the utilization of scarce frequency bands in 5G networks.

1.2 Problem Statement

One of the key challenges in beamforming optimization is the need to effectively harness the wealth of data available from beamforming feedback datasets to inform and guide the beamforming process.

Moreover, traditional beamforming techniques often rely on static rules and predetermined thresholds to make beamforming decisions, which may not fully exploit the rich information embedded in beamforming feedback datasets. As a result, there is a pressing need to explore innovative approaches that can leverage advanced data analytics and machine learning techniques to extract actionable insights from beamforming feedback datasets and optimize beam directionality in a dynamic and adaptive manner.

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Therefore, the primary objective of this research is to address the limitations of traditional beamforming techniques by integrating machi learning algorithms into the beamformi optimization process. By harnessing the power machine learning, we aim to develop intellige beamforming solutions that can automatically lea from data, adapt to changing network conditior and optimize beam directionality.

1.3 Research Contribution

This research made significant contributions advancing beamforming strategies in mobi networks through the analysis of beamformi feedback datasets and the application of machi learning techniques. Specifically, we focused (utilizing Support Vector Machines (SVM) categorize beams based on their strength, therel enabling the selection of optimal line-of-sig (LOS) beams for improved 5G beamformi performance. The primary contributions can l summarized as follows:

Integration of Machine Learning wi Beamforming Optimization: The researc proposes the integration of machine learnii techniques, particularly Support Vector Machin (SVM), with beamforming optimization in mobi networks. This integration represents a nov approach that leverages data-driven insights enhance the efficiency and reliability of wirele communication systems. By analyzi beamforming feedback datasets and categorizi beams into distinct strength categories using SVI the research introduces a new paradigm f optimizing beam directionality in 5G networks.

Adaptive Beamforming Algorithm: The researc introduces an adaptive beamforming algorith designed to dynamically adjust the direction beams based on the strength of received signal thereby augmenting communication quality ai efficiency. This adaptive algorithm represents significant departure from traditional stat beamforming techniques, offering the potential f real-time optimization and adaptation to changii network conditions.

2. LITERATURE SURVEY

- In this study, they introduce integrated algorithms for the simultaneous optimization of analog beam selection (using the sum-rate metric) and digital precoders [1]. These joint designs incorporate multiple initializations, iterations, and selection features, along with the implementation of Block Coordinate Descent (BCC). Consequently, the achieved network sum-rate gains significantly surpass those of a simplistic disjoint design, where analog beam selection is based on the DL power metric and digital precoders are optimized independently. Subsequently, they present supervised machine learning (ML) algorithms trained using beam selection decisions derived from the well-constructed joint design algorithms. The numerical results obtained through the RFt algorithm are promising, as it can retrain 99-100% of the original sum-rate results achieved by the integrated design algorithms. The research focuses on millimeter wave cell-free massive MIMO systems, which may not be generalizable to other MIMO configurations. The study utilizes supervised machine learning, leaving room for exploration of unsupervised or reinforcement learning approaches.

- They have conducted a comprehensive investigation into machine learning (ML) methods for addressing the beam selection challenge in 5G/B5G networks [2]. Their presentation encompasses a thorough framework outlining strategies to enhance classification accuracy. Remarkably, the accuracy of their findings surpasses 92%, achieved through diverse ML models and the incorporation of the SMOTE-NC algorithm to address class imbalance. Notably, both deep learning (DL) models yielded results with accuracy exceeding 90%. However, the most notable accuracy values were attained through the utilization of ensemble learning techniques. This outcome aligns with expectations, as ensemble methods have the potential to outperform individual learners. Particularly, both voting classifiers demonstrated results with accuracy surpassing 95%. The work compares machine learning algorithms for beam selection but doesn't explore how these algorithms can be improved for specific network scenarios.

- This paper introduces a beam selection scheme and a multi-cell cooperation beamforming (BF) scheme based on Polarization-based Feedback and Precoding (PFP) in cellular millimeter-wave (mmWave) heterogeneous networks with densely deployed small cells [3]. The approach capitalizes on the transmission characteristics of mmWave technology. In comparison to existing beam selection algorithms, the PFP-based scheme proposed in this paper mitigates the computational complexity associated with exhaustive search algorithms, concurrently minimizing feedback requirements. Notably, the presented multi-cell cooperation scheme proves effective in mitigating inter-cell beam interference within mmWave heterogeneous networks, thereby enhancing the overall system sum-rate. This research investigates position fingerprint-based beam selection, limiting its applicability to scenarios where user location is readily available.

- This paper primarily introduces a novel rapid machine learning algorithm designed for 3-dimensional UAV beams [4]. It extensively explores the utilization of bandits, a concept gaining traction in contemporary computing, especially in domains such as social networking and service delivery. The envisioned proliferation of smart entities, including smart cities and smart homes, among others, is a driving force for extending this research. Their commitment extends beyond conventional boundaries, focusing on technological advancements. Specifically, the aim is to address concerns related to unnecessary data capturing, a growing issue, through beam emission tracking. This aligns with global discussions on network regulations and laws, marking a concerted effort to contribute to the responsible evolution of this technology. The study concentrates on beam selection for UAV applications, and its effectiveness in other mobile network use cases remains unexplored.

The prediction outcomes indicated that the proposed RF model exhibited higher accuracy than empirical formulas [5]. The findings also underscored the significance of geometric and concrete properties of beams in the learning process. This study successfully developed a reliable and robust soft computing model for predicting the Vs value of RC beams, making a noteworthy contribution to the foundational knowledge of structural engineering design and sustainability. This reference focuses on a different application of machine learning (beam shear strength prediction) and doesn't address beam selection challenges.

In this investigation, a Deep Neural Network (DNN) is integrated into the computation of the resonant frequency of Beam-Steering Phased Array Antennas (BSPAs), leading to the development of a DNN-based soft computing framework within a comprehensive full-wave 3D Electromagnetic (EM) analysis platform [6]. The network is trained using a set of input-output data pairs generated through the Modified Gravitational Search Algorithm with Particle Swarm Optimization (MGSA-PSO) algorithm. A database is established, encompassing the resonant frequency data from simulations involving 150 BSPAs with varied geometry and electrical parameters. The resulting DNN model proves to be highly effective in estimating resonant frequencies with exceptional precision, presenting itself as a cost-efficient and potentially advantageous alternative to both expensive measurements and extensive simulations. Furthermore, the developed DNN model is employed to dynamically steer the radiation pattern of the designed antenna array. The results indicate a noteworthy agreement between the specified performance criteria and the synthesized outcomes, validating the efficacy of the DNN-based approach. While this work explores deep learning for beam steering, it doesn't delve into beam selection itself.

In this research paper a deep learning-based resource allocation approach tailored for massive multiple-input-multiple-output (MIMO) communication systems [7]. The scenario involves a base station (BS) equipped with a large-scale antenna array engaged in communication with a user equipment (UE) through beamforming techniques. Our proposed method, termed Deep Scanning, leverages deep Q-learning to identify a near-optimal beamforming vector efficiently. Through extensive simulations, the proposed Deep Scanning approach successfully identifies the optimal beam vector with a high probability. Additionally, the results demonstrate a noteworthy reduction in the computational complexity required to determine the optimum beam vector, as compared to traditional beam search schemes. This suggests that Deep Scanning offers a more efficient and effective solution for beamforming in massive MIMO communication systems. The research utilizes deep reinforcement learning, but a comparison with other learning approaches for beam selection in massive MIMO systems is missing.

This paper addresses the cell-discovery problem in 5G millimeter-wave (mmWave) communication systems, focusing on the utilization of the multiple input, multiple output (MIMO) beam-forming technique [8]. The primary objective is to optimize beam selection methods by

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incorporating user-equipment context-awareness, aiming to reduce latency in beam/cell identification. Given the high path-loss in mmWave systems, the beam-forming technique is crucial for enhancing the Signal-to-Noise Ratio (SNR). When extending the user discovery distance, narrow beams are necessary, leading to a significant increase in the number of potential beam orientations and the time required for discovery when employing a random scanning approach. The proposed solution revolves around reducing latency by integrating artificial intelligence (AI) or machine learning (ML) algorithms to predict the optimal beam orientation based on context information from the Global Navigation Satellite System (GNSS), lidars, and cameras. This reference investigates machine learning for beam selection but lacks exploration of how these techniques can be optimized for specific network conditions.

- Numerous survey papers in the literature explore diverse aspects of machine learning (ML) applications in future wireless networks. The authors of [9] delve into the subject of antenna design for forthcoming networks using ML. Conversely, [10] investigates ML applications in vehicular networks from a networking perspective. Within the same context, a comprehensive overview of various ML techniques applied to communication, network, and security components in vehicular networks can be found in [11,12]. In a recent study [13] outlines the latest developments in deep learning-based physical layer methods, aiming to pave the way for emerging applications of 6G. These references focus on applying machine learning to vehicular networks, not specifically beam selection in communication systems.

In [14], the authors introduce FusionNet, a dual-input neural network designed to predict the optimal beam by incorporating information from both sub-6 GHz channels. They employ a deep learning approach to activate antennas operating in the mmWave band. FusionNet exhibits superior performance compared to traditional fully connected neural networks and established sub-6 GHz strategies, showcasing enhanced accuracy in predictions and improved achievable rates. The research explores beam prediction using fusion of sub-6 GHz channels, but doesn't directly address beam selection itself.

In their work detailed in [15], the authors crafted deep learning architectures capable of predicting a set of top-K beam pairs, leveraging non-RF sensor data such as GPS, camera, and LiDAR. This approach resulted in a notable improvement in prediction accuracy ranging from 3.32% to 43.9%. The authors introduced a fusion network that demonstrated a 20–22% enhancement in top-10 accuracy when compared to other state-of-the-art techniques. Furthermore, they addressed the beam selection process by formulating an optimization problem for choosing the set of K candidate beam pairs, leading to a remarkable reduction in beam selection time by 95–96%. This reference focuses on deep learning for multi-modal sensor data in vehicular networks, not beam selection in communication systems.

3. BEAMFORMING TECHNIQUES

In mobile computing, beamforming is particularly beneficial for improving the reliability and speed of connections, especially in scenarios where devices are in motion or experiencing varying signal conditions. By dynamically adjusting the direction of the transmitted or received signals, beamforming helps maintain a stable and robust wireless link, leading to better performance and user experience in mobile devices such as smartphones and tablets.

In the ever-expanding realm of mobile telecommunication, the optimization of beamforming strategies plays a pivotal role in ensuring efficient and robust wireless communication. This proposed model aims to investigate and enhance the process of beamforming in mobile networks by focusing on the analysis of beamforming feedback datasets. The central objective is to leverage machine learning techniques, specifically Support Vector Machines (SVM), to categorize beams into weak and strong categories, subsequently employing a adaptive beamforming algorithm to identify and select the optimal line-of-sight (LOS) available beam.

3.1 Beam Steering

Beam steering, in the context of mobile computing, refers to a technique used to enhance wireless communication performance. It involves focusing radio frequency signals in specific directions, optimizing the transmission and reception of data between devices. This directional approach improves the signal quality, reduces interference, and enhances overall communication efficiency in wireless networks.

3.1.1 **dataset collection**

The primary objective of this study is to undertake a comprehensive beamforming feedback dataset collection from users within a simulated environment. By engaging users in different scenarios and gathering their feedback, we aim to evaluate the performance of beamforming algorithms under diverse conditions and identify areas for improvement. Gather qualitative and quantitative feedback from users regarding their experience with 5G connectivity in the simulated environment. Record metrics such as Beam ID, Bandwidth (MHz), Throughput (Mbps), Packet Delivery Ratio, End-to-End Delay (ms), signal strength. Next we have to evaluate the performance of adaptive beamforming algorithms in response to user feedback and analyze how beamforming strategies adapt to changes in user density, mobility, and environmental factors.

3.1.2 SVM analysis

The main components are:

- To implement SVM, a powerful machine learning algorithm.
- Train the SVM model using the annotated dataset to learn the patterns distinguishing weak and strong beams.
- Classify beams into weak and strong categories based on the learned patterns from the dataset.

➢ **Training the SVM Model with Annotated Dataset:**

The annotated dataset should be divided into a training set and a testing set. The training set is used to teach the SVM model, while the testing set serves as an independent dataset to assess the model's generalization ability. During the training phase, SVM leverages the annotated information to identify and internalize the intricate relationships and dependencies that characterize weak and strong beams. This process involves adjusting the model's parameters to create an optimal decision boundary that aligns with the inherent patterns present in the dataset.

➢ **Unveiling Patterns to Classify Beams:**

Once trained, the SVM model transforms into a powerful tool capable of classifying beams based on the patterns it has learned. By analyzing the feature space defined by performance metrics such as Beam ID, Bandwidth, Throughput, Packet Delivery Ratio, End-to-End Delay, and signal strength, SVM discerns the subtle nuances that distinguish weak and strong beams. The model's ability to generalize from the training data ensures that it can accurately categorize beams in new, unseen scenarios, contributing to a comprehensive understanding of beamforming efficiency. The testing dataset comprises instances not seen during the training phase. This setup enables the assessment of how well the SVM model generalizes its learning to new, previously unseen beamforming scenarios.

➢ **Categorizing Beams into Weak and Strong Classes:**

In the classification phase, the SVM model applies the acquired knowledge to categorize beams into weak and strong classes. This classification is driven by the model's ability to recognize previously unseen patterns and make informed decisions based on the identified features. The result is a clear distinction between beams that exhibit optimal performance characteristics and those that fall short, providing valuable insights into the strengths and weaknesses of specific beamforming strategies.

➢ **Pattern Change of Beam Direction:**

For the "weak" category, the beamforming system can dynamically change the beam direction patterns to adapt to the changing radio environment. This adaptation could involve continuously monitoring the signal quality and adjusting the beam direction to optimize the communication link for users in the "weak" category. The goal is to ensure a robust and reliable connection for users even in challenging signal conditions.

➢ **Formation of Beams from Strong Category:**

Beams classified as "strong" indicate favorable signal conditions. The system aims to maintain and optimize the communication link for users associated with strong beams, ensuring a stable and high-quality connection. This prioritization strategy allows for efficient allocation of resources, focusing on users with robust signal strengths to enhance overall network performance.

3.2 Adaptive Beamforming Algorithm for LOS

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Beam Selection:

Determining line-of-sight (LOS) availability for a particular user in beamforming involves assessing the visibility between the user and the base station. LOS conditions are crucial for effective beamforming, as direct visibility facilitates stronger and more reliable signal transmission. Understand atmospheric conditions that may cause signal refraction. While refraction can bend signals and enable communication beyond the visual line of sight, it may not always guarantee true LOS conditions. So the main objective is to:

- Develop a adaptive beamforming algorithm to further refine the selection process, specifically focusing on identifying and isolating line-of-sight (LOS) available beams among the strong category.
- Consider factors such as beam directionality and interference levels in the decision-making process.

Algorithm

1. Initial Beamforming Weights:
   Initial Weights = ComputeWeights (initial(w)=0)
2. Steering vector calculation.
   Steering vector = exp(-j$\frac{2\pi d}{\lambda}\sin\theta$)
3. Directivity (D) Calculation. D= $\frac{4\pi}{\Omega}$
4. Beamforming Gain G= $\frac{D}{10}$
5. Effective Isotropic Radiated Power (EIRP):
   EIRP=Transmit Power+G
6. LOS/NLOS Classification:
   if (EIRP > EIRP_threshold) then
   LOS_condition = true
   UpdateWeights = 1
   else
   LOS_condition = false
   UpdateWeights = 0

The algorithm presented involves two main components: Effective Isotropic Radiated Power (EIRP) calculation and Line-of-Sight (LOS) or Non-Line-of-Sight (NLOS) classification based on a threshold.

EIRP Calculation: The Effective Isotropic Radiated Power (EIRP) is computed using the formula EIRP = Transmit Power + G, where "Transmit Power" represents the power emitted by the transmitter, and "G" stands for the antenna gain. The algorithm checks if the calculated EIRP is greater than a specified threshold (EIRP_threshold).

- If EIRP > EIRP_threshold:

Set LOS_condition to true: This indicates that the communication link is considered to be in Line-of-Sight.

Set UpdateWeights to 1: This suggests that weights or parameters associated with the communication system should be updated or adjusted.

- Else:

Set LOS_condition to false: In this case, the communication link is classified as Non-Line-of-Sight.

Set UpdateWeights to 0: There is no need to update weights or parameters since the LOS condition is not met.

- Apply Beamforming:

Utilize the updated weights to form the beam and steer it in the direction of the user signal:

- Repeat:

Continuously repeat the monitoring and adaptive weight update process as the user moves or signal conditions change.

4. SIMULATION ENVIRONMENT

The work is implemented in NS3 and the parameters are displayed in Table 1. In the pursuit of advancing the understanding and optimization of network slicing in 5G the simulation environment plays a pivotal role in providing a controlled, scalable, and reproducible platform for experimentation and analysis. This section delineates the architecture, components, and key parameters of the simulation environment employed in this research, with a focus on evaluating SIR, BER, and E2E delay.

Table1. Simulation Parameters

Parameter	**Value**
	Small cells

Number of cells	50
Cell radius (m)	100
Cell height (m)	15
Transmit Power (dBm)	26
Simulation area	8×8 km^2
Number of EUs	300
EU height (m)	1.5
Mobility model	Random Waypoint Model
Simulation time (s)	600
EU speed (meter/second)	20,40,60,80,100
Thermal noise density (dbm/Hz)	-174
Noise figure of EU (dB)	9
Time to trigger (ms)	Adaptive

5. PERFORMANCE EVALUATION

The simulation results for the 5G beamforming study presented in this research paper demonstrate the efficacy of employing beam direction support vector machines (SVM) and adaptive beamforming algorithms for enhancing the performance of wireless communication systems. By leveraging beamforming techniques, we aimed to optimize communication links in scenarios where directional transmission is crucial for achieving high data rates, reducing interference, and improving overall network efficiency. SNR, BER, and e2e delay are key parameters in evaluating the performance and reliability of communication systems. Understanding these parameters and their associated formulas allows for a comprehensive analysis and optimization of communication networks in various applications. The overall performance of the proposed beamforming strategy is evaluated by comparing it to traditional methods[3] [6] and the impact of the adaptive algorithm on selecting optimal LOS beams for communication is determined.

5.1 Signal-to-Noise Ratio (SNR)

- (SNR) is a measure to quantify the ratio of the strength of a desired signal to the strength of background noise. In the context of communication systems, a higher SNR generally indicates a better-quality signal.
- The signal and noise are measured in decibels (dB), so the Signal-to-Noise Ratio (SNR) formula is as follows:
- SNR(dB)=Signal(dB)−Noise(dB)

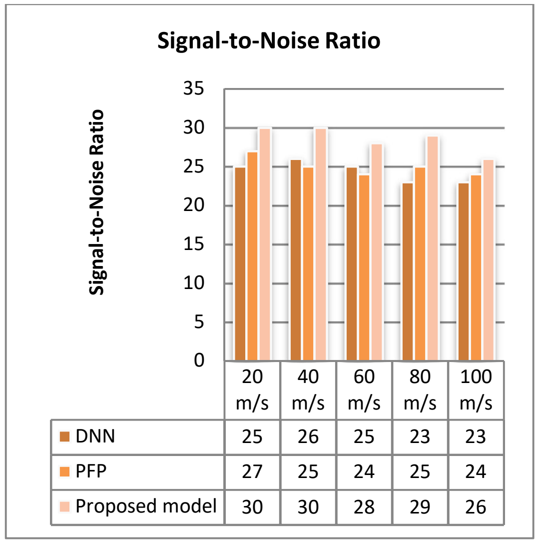

Figure 1 - SNR

Here are some key reasons highlighting the importance of finding SNR:

- Quality of Communication: SNR directly impacts the quality of the communication signal. A higher SNR generally indicates a stronger signal relative to noise, leading to better communication quality and reliability.
- Object Detection and Tracking: In radar and sensing applications, SNR is vital for detecting and tracking objects. A higher SNR improves the accuracy and reliability of target detection in radar systems.
- Data Rate and Throughput: SNR affects the achievable data rate and throughput in communication systems. Higher SNR allows for more efficient transmission of data.

5.2 Bit Error Rate (BER)

Bit Error Rate (BER) is a metric that quantifies the percentage of bits transmitted in error compared to the total number of bits transmitted. It is a critical parameter for assessing the reliability and performance of digital communication systems. BER is expressed and represents the ratio of incorrectly received bits to the total number of transmitted bits. A lower BER indicates higher data transmission accuracy and system reliability.

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$$\text{BER} = \left(\frac{\textit{Number of bits in error}}{\textit{Total transmitted bits}}\right)$$

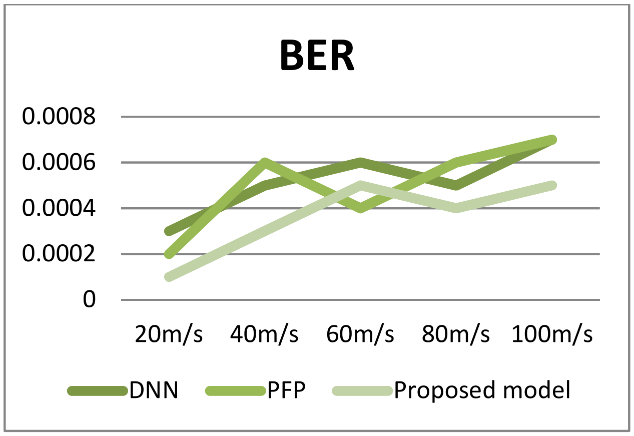


Figure 2 - BER

The Bit Error Rate (BER) is a critical metric in communication systems, and its importance stems from several key aspects:

- Impact on Wireless Networks: In wireless communication and optical communication systems, the BER directly influences the reliability of data transmission. It is crucial in determining the performance of these systems in noisy or challenging environments.
- Data Integrity: In networking, especially in high-speed data transmission, maintaining low BER is vital for ensuring the integrity of transmitted data. This is crucial in applications such as data centers and telecommunications networks.

5.3 End-to-End Delay Examination

This section delves into the evaluation of end-to-end delay, measuring the time it takes for a packet to travel from the source to the destination. The analysis considers the impact of beamforming on latency under diverse scenarios, including scenarios with varying user mobility, network congestion, and interference.

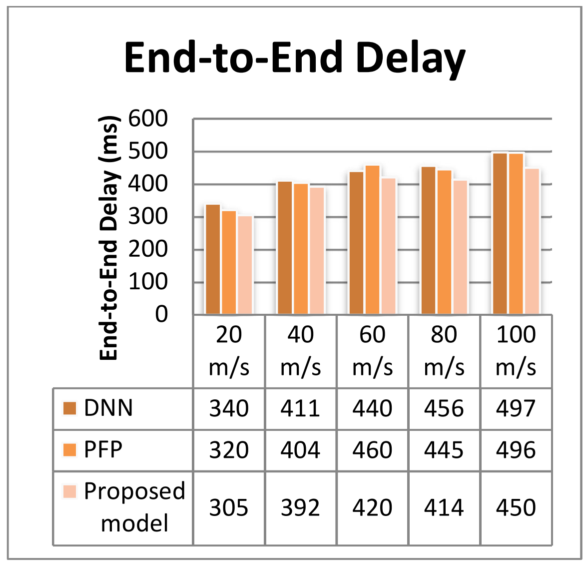
End-to-End Delay=Transmission Delay + Propagation Delay + Queuing Delay + Processing Delay

Transmission Delay: Time taken to push the packet's bits into the link.

Propagation Delay: Time taken for the signal to travel from the source to the destination.

Queuing Delay: Time spent waiting in the queue before transmission.

Processing Delay: Time taken by the routers or switches to process the packet.



	20 m/s	40 m/s	60 m/s	80 m/s	100 m/s
DNN	340	411	440	456	497
PFP	320	404	460	445	496
Proposed model	305	392	420	414	450

Figure 3 – End-to-End Delay

Here are several reasons highlighting the importance of measuring and managing end-to-end delay:

- Voice and Video Communication: In real-time communication applications such as VoIP and video conferencing, low E2E delay is critical to provide a natural and seamless user experience. High delays can lead to noticeable lag and impact the quality of conversations.
- Gaming: In online gaming, where responsiveness is crucial, minimizing E2E delay is essential to provide players with a more immersive and enjoyable gaming experience. High delays can result in delayed actions and affect gameplay.
- Automation and Robotics: In industrial settings, where automation and robotics are prevalent, low E2E delay is vital for ensuring

timely and precise control of machinery and processes. Delays can impact the efficiency and safety of industrial operations.

Pros:

- The research addresses a highly relevant and critical aspect of mobile telecommunication, emphasizing the importance of optimizing beamforming strategies for the efficiency and robustness of wireless communication networks, particularly in the context of 5G networks.
- The proposed model outlines an innovative approach that integrates machine learning techniques, specifically Support Vector Machines (SVM), for beam classification, and proposes an adaptive beamforming algorithm to enhance the performance of 5G beamforming. The adaptive algorithm, showcasing a holistic approach towards optimizing beam directionality in 5G networks, which has the potential to significantly enhance communication quality and reliability.
- By focusing on parameters such as interference level, bit error rate, and latency, the research aims to evaluate the performance and reliability of communication systems, indicating its practical implications for improving the quality and efficiency of 5G networks.

Cons:

- Utilizing beamforming feedback datasets for machine learning model training raises concerns about user privacy. Unauthorized access to or misuse of such data could compromise user privacy and lead to privacy breaches.
- Without proper encryption mechanisms and access controls, these datasets may be vulnerable to unauthorized access, interception, or tampering, potentially leading to data breaches or manipulation of network performance.
- Machine learning models used for beam classification and adaptive beamforming algorithms may be susceptible to adversarial attacks.

6. CONCLUSION AND FUTURE SCOPE

In our investigation, the utilization of beam direction SVM showcased promising results in dynamically determining the optimal beam direction for transmission. This approach harnessed the power of machine learning to adaptively select beam directions, taking into account the dynamic nature of the wireless environment. The SVM-based beam direction strategy exhibited the ability to adapt to changing channel conditions, enhancing the robustness and adaptability of the 5G communication system. Furthermore, our research explored the application of adaptive beamforming algorithms for beam selection in line-of-sight (LOS) scenarios. The adaptive beamforming algorithm considered the availability of line-of-sight paths, intelligently selecting beams to capitalize on LOS links and capitalize on the advantages they offer, such as reduced signal attenuation and enhanced reliability. This approach showcased improved performance in LOS environments, highlighting the significance of tailoring beamforming strategies to the specific characteristics of the communication channel. In conclusion, the simulation results affirm the potential of beamforming techniques in the context of 5G wireless communication systems. The combination of beam direction SVM and adaptive beamforming algorithms contributes to the optimization of beamforming strategies, enabling the system to dynamically adapt to diverse channel conditions. These findings underscore the importance of intelligent beamforming techniques in realizing the full potential of 5G networks, especially in scenarios where directional transmission and LOS links play a critical role in achieving high-performance communication. As mobile technology continues to evolve, the insights gained from this research can inform the development of advanced beamforming strategies for future wireless communication systems.

As mobile networks become increasingly reliant on machine learning and data-driven optimization techniques, addressing security and privacy concerns becomes paramount. Developing techniques to mitigate privacy risks while preserving the effectiveness of beamforming optimization is crucial for ensuring the trustworthiness and security of 5G networks.

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CONTRIBUTION STATEMENT

A. Priyanka: Conceptualization, Methodology, Software, Investigation, Resources, Writing – original draft, Writing – review & editing, Visualization, Project administration, Funding acquisition.
C. Chandrasekar: Validation, Supervision.
M. Ashok kumar: Formal analysis.

REFERENCES

[1] Yetis, Cenk M.; Björnson, Emil; Giselsson, Pontus, "Joint Analog Beam Selection and Digital Beamforming in Millimeter Wave Cell-Free Massive MIMO Systems" TechRxiv. Preprint. https://doi.org/10.36227/techrxiv.14562177.v1, May 2021.
[2] Efstratios Chatzoglou 1 and Sotirios K. Goudos 2,, "Beam-Selection for 5G/B5G Networks Using Machine Learning: A Comparative Study", Sensors, Mar 2023.
[3] Zufan Zhang and Yanbo Chen, "Position Fingerprint-Based Beam Selection in MillimeterWave Heterogeneous Networks", Sensors, Sep 2017.
[4] Hao Meng, Wasswa Shafik , S. Mojtaba Matinkhah , and Zubair Ahmad, "A 5G Beam Selection Machine Learning Algorithm for Unmanned Aerial Vehicle Applications", Wireless Communications and Mobile Computing, Aug 2020.
[5] Hayder Riyadh Mohammed Mohammed and Sumarni Ismail, "Random Forest versus Support Vector Machine Models Applicability for Predicting Beam Shear Strength", Complexity, Jun 2021.
[6] Ahmed M. Montaser, Korany R. Mahmoud, "Deep Learning Based Antenna Design and Beam-Steering Capabilities for Millimeter-Wave Applications", IEEE, DOI 10.1109/ACCESS.2021.3123219.
[7] Minhoe Kim, Woongsup Lee, and Dong-Ho Cho, "Deep Scanning—Beam Selection Based on Deep Reinforcement Learning in Massive MIMO Wireless Communication System", *Electronics, Nov 2020.*
[8] Julius Ruseckas, Gediminas Molis, and Hanna Bogucka, "MIMO Beam Selection in 5G Using Neural Networks", International Journal Of Electronics and Telecommunications, Nov, 2021.
[9] Khan, M.; Hossain, S.; Mozumdar, P.; Akter, S.; Ashique, R. A review on machine learning and deep learning for various antenna design applications. Heliyon 2022.
[10] Tan, K.; Bremner, D.; Le Kernec, J.; Zhang, L.; Imran, M. Machine learning in vehicular networking: An overview. Digit. Commun. Netw. 2022, 8, 18–24.
[11] Tang, F.; Mao, B.; Kato, N.; Gui, G. Comprehensive survey on machine learning in vehicular network: Technology, applications and challenges. IEEE Commun. Surv. Tutor. 2021, 23.
[12] Tang, F.; Kawamoto, Y.; Kato, N.; Liu, J. Future Intelligent and Secure Vehicular Network Toward 6G: Machine-Learning Approaches. Proc. IEEE 2020, 108, 292–307.
[13] Ozpoyraz, B.; Dogukan, A.; Gevez, Y.; Altun, U.; Basar, E. Deep Learning-Aided 6GWireless Networks: A Comprehensive Survey of Revolutionary PHY Architectures. IEEE Open J. Commun. Soc. 2022, 3, 1749–1809.
[14] Gao, F.; Lin, B.; Bian, C.; Zhou, T.; Qian, J.; Wang, H. FusionNet: Enhanced Beam Prediction for mmWave Communications Using Sub-6 GHz Channel and a Few Pilots. IEEE Trans. Commun. 2021, 69, 8488–8500.
[15] Salehi, B.; Reus-Muns, G.; Roy, D.;Wang, Z.; Jian, T.; Dy, J.; Ioannidis, S.; Chowdhury, K. Deep Learning on Multimodal Sensor Data at the Wireless Edge for Vehicular Network. IEEE Trans. Veh. Technol. 2022, 71, 7639–7655.