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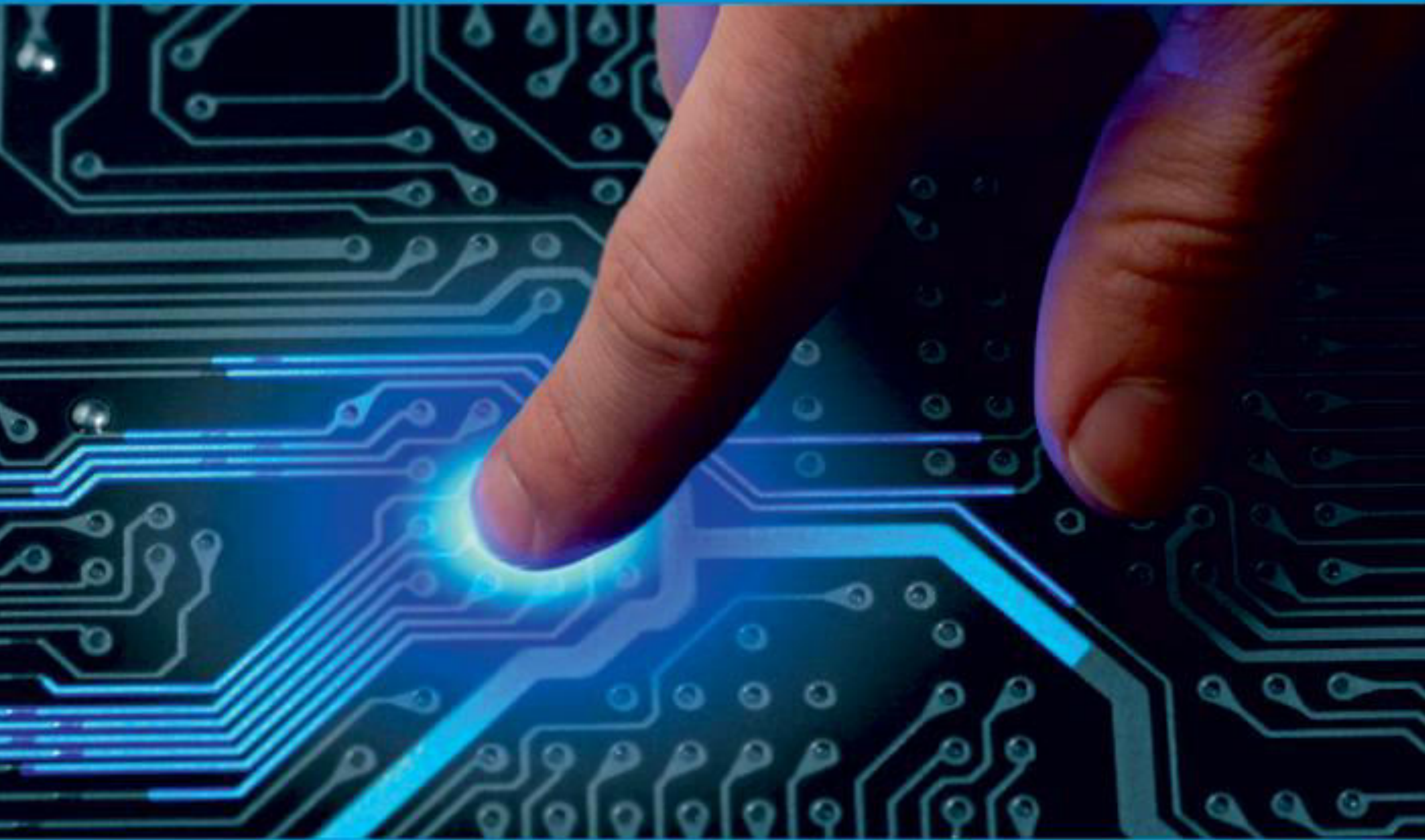

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Massive System for IOT Application using Channel Estimation Technique: A Review

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ABSTRACT: In the recent years more research is going on in 5G technology. Massive MIMO (large-scale antenna systems, covering hyper MIMO) is more attractive and different from current practice in 4G technology, through the preferred use of more service antennas over active terminals and time-division, frequency division duplex operations. More number of Antennas can be used for the channel state information (CSI) estimation. To provide high performance in 5G cellular networks, Massive MIMO is one of the promising methods with simple transmit and receive operations. But it is possible only with accurate channel state information at the transmitter. Because of usage of large dimensional channels is one of the challenging issues in current research. In this paper the study of different channels estimation technique for massive system.

KEYWORDS: Massive MIMO, CSI, Channel Estimation

I. INTRODUCTION

The acquisition of accurate channel state information (CSI) is essential in millimeterwave (mmWave) massive MIMO systems [1]. Hence, how to reliably and efficiently acquire CSI is a fundamental issue to fully exploit the potential advantages of mmWave massive MIMO systems. Compared with conventional mmWave communications and massive MIMO working at sub-3–6 GHz, channel estimation (CE) in mmWave massive MIMO systems is more challenging mainly due to the following reasons. 1. The number of antennas in mmWave massive MIMO can be very large. In mmWave massive MIMO systems, the number of antennas at both the base station (BS) and mobile station (MS) can be much larger than that in conventional massive MIMO working at sub-3–6 GHz due to the much smaller wavelength of mmWave signals [2]. This implies the challenge that CE in mmWave massive MIMO can be more difficult even when time division duplex (TDD) leveraging the channel reciprocity is considered, since the user side may also employ dozens of antennas. Hence, mmWave massive MIMO systems may suffer from the prohibitively high pilot overhead for CE. It should be also pointed out that even for TDD-based communication systems, synchronization, calibration error of radio frequency (RF) chains, and other issues to guarantee the channel reciprocity are not trivial, especially in mmWave communications [1]. 2. mmWave communications suffer from the special hardware constraints. The hardware cost and energy consumption of transceivers, including high-speed analog-to-digital convertors (ADCs) and digital-to-analog convertors, synthesizers, mixers, and so on, in mmWave communications are much larger than those in conventional cellular communications. Hence, massive low-cost antennas but a limited number of expensive RF chains can be an appealing transceiver structure for mmWave massive MIMO systems [1–4], which will be further illustrated in Section 6.2.2. Such a transceiver structure makes the CE more challenging. Due to the much smaller number of RF chains than that of antennas, it is difficult to exploit the effective observations of small size to estimate the mmWave massive MIMO channels of large size. 3. The signal-to-noise ratio (SNR) before beamforming is low in mmWave communications. In mmWave communications, the bandwidth can be hundreds of megahertz or even multiple gigahertzes, which will introduce much more thermal noise [1]. Moreover, due to the strong signal directivity of mmWave, the low SNR before beamforming also makes the CE more difficult [2]. Because reliable CE usually requires sufficient SNR, it indicates that at least partial channel state information at the transmitter (CSIT) may be required to ensure beamforming at the transmitter to match mmWave MIMO channels for reliable CE. Hence, CE in mmWave massive MIMO systems should consider not only signal processing in the digital baseband, but also the characteristics of analog phase-shift networks (PSNs) in the analog RF, which can make CE more complex. Finally, the Doppler shift in mmWave can be more obvious due to the high frequency band, and the blockage effect should also be considered [1].

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II. BACKGROUND

Industry experts as well as academicians/researchers in the communication field form all parts of the globe are working for increasing system capacity to meet the demands of new services with increased amount of data exchange, uninterrupted connectivity and seamless service quality. The three predominant design aspects listed as under are currently under investigation by industry experts to realize anticipated increase in system capacity as compared to current wireless standard.

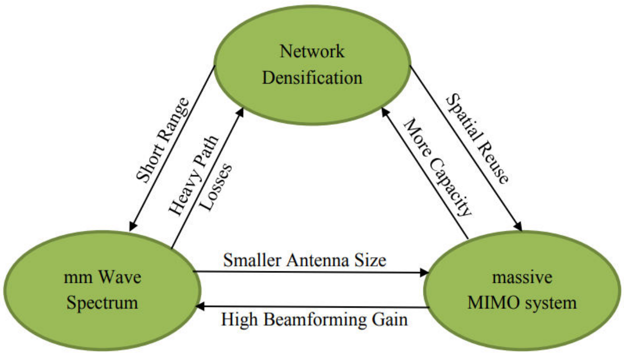

Figure 1: Relation between Three-design Aspects for Upcoming Wireless Communication Systems

- Millimeter Wave Spectrum - Shift towards higher available bandwidth
- Massive MIMO and Beamforming. - Higher Spectral Efficiency
- Small Cells - Network densification to overcome heavy path losses

The before stated three predominant design characteristics are technically interconnected with each other in several ways. The drift towards millimeter Waves will facilitate the utilization of reasonably large available bandwidth in licensed as well as unlicensed spectrum to realize anticipated system capacity. As millimeter Waves has relatively much shorter wavelengths, because of it the physical dimensions of an antenna and hence the antenna array will reduce significantly. Consequently, we will be able to fabricate the relatively large number of antenna elements in comparatively smaller physical dimensions and encourages for the utilization of large dimensional massive MIMO systems. In addition, the Small Cell Technology [3, 4] will enable us to conquer with hefty path losses linked with millimeter Wave communication. Industry experts/Academicians/Researcher are working on all three design aspects to realize anticipated increase in system capacity for 5G and other upcoming wireless communication applications/standards. The figure 1 presents a symbolic view of the evolution of associated user services from 2G to 5G.

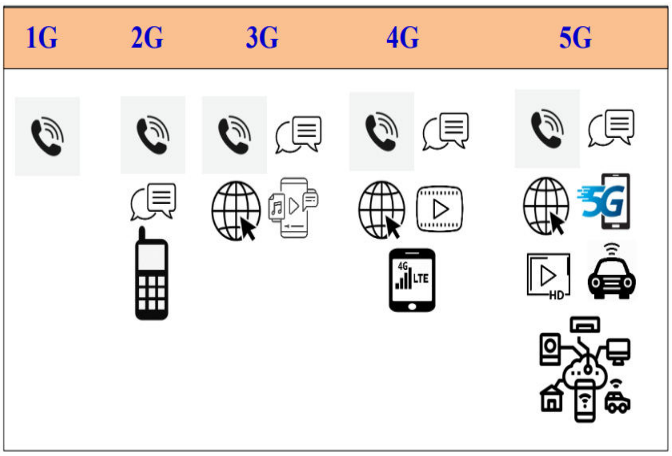

Figure 2: Evolution of Services form 2G to 5G

The upcoming wireless communication applications/standards targets both public and private sectors. These also support diverse nature of devices and associated technologies.

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III. LITERATURE REVIEW

Farzana Kulsoom et al. [1], accurate channel state information (CSI) at the transmitter is an essential prerequisite for transmit beamforming in massive multiple input multiple output (MIMO) systems. However, due to a large number of antennas in massive MIMO systems, the pilot training and feedback overhead become a bottleneck. To resolve this issue, the research work presents a novel framework for frequency division duplex (FDD) based multi-user massive MIMO system. A 2-step quantization technique is employed at the user equipment (UE) and the CSI is recovered at the base station (BS) by applying the proposed compressed sensing (CS) based algorithms. The received compressed pilots are quantized by preserving 1 bit per dimension direction information as well as the partial amplitude information. Subsequently, this information is fed back to the BS, which employs the proposed quantized partially joint orthogonal matching pursuit (Q-PJOMP) or quantized partially joint iterative hard thresholding (Q-PJIHT) CS algorithms to recover the CSI from a limited and quantized feedback. Indeed, an appropriate dictionary and the hidden joint channel sparsity structure among users is exploited by the CS methods, resulting in the reduction of the feedback information required for channel estimation. Simulations are performed using singular value decomposition (SVD) and minimum mean square error (MMSE) beamforming utilizing the estimated channel. The results confirm that the proposed 2-step quantization approaches the system with channel knowledge without quantization, thus overcoming the training and feedback overhead problem. Moreover, the proposed 2-step quantization outperforms 1-bit quantization, at the cost of slightly higher complexity.

Mustafa S. Aljumaily et al. [2], hybrid Beamforming has been used in wireless communications for many years. With the fifth generation of wireless communications or (5G) and beyond networks, the need for beamforming is ever increasing because of the use of higher frequencies and the need to provide better coverage and better spectral utilization. Although many designs have been suggested to build hybrid beamforming, the Machine Learning (ML) based designs have attracted much attention recently because of the flexibility in coping with the wireless channel variations and user mobility they can attain when directing the transmission to the right direction during the communication process. In this paper, we describe the extended design of machine learning based hybrid beamforming for multiple users in systems that use millimeter waves (mmWaves) and massive MIMO architectures. The simulation results show that with the right amount of training data samples (channel feedback), the ML based hybrid beamforming architecture can achieve the same spectral efficiency (bits/sec/Hz) as the fully digital beamforming designs with negligible error for both single user and multi-user Massive-MIMO scenarios.

Osama I. et al. [3], Millimeter wave (mmWave) massive multiple-input multiple-output (MIMO) has been regarded to be an emerging solution for the next generation of communications, in which hybrid analog and digital precoding is an important method for reducing the hardware complexity and energy consumption associated with mixed signal components. However, the fundamental limitations of the existing hybrid precoding schemes are that they have high-computational complexity and fail to fully exploit the spatial information. To overcome these limitations, this paper proposes a deep-learning-enabled mmWave massive MIMO framework for effective hybrid precoding, in which each selection of the precoders for obtaining the optimized decoder is regarded as a mapping relation in the deep neural network (DNN). Specifically, the hybrid precoder is selected through training based on the DNN for optimizing precoding process of the mmWave massive MIMO. Additionally, we present extensive simulation results to validate the excellent performance of the proposed scheme. The results exhibit that the DNN-based approach is capable of minimizing the bit error ratio and enhancing the spectrum efficiency of the mmWave massive MIMO, which achieves better performance in hybrid precoding compared with conventional schemes while substantially reducing the required computational complexity.

T. Kebede et al. [4], the fifth-generation (5G) wireless communication system requires massive connectivity with high data rates and low latency. One of the technologies to meet these requirements is mm Wave massive MIMO. This work, therefore, aspires to have an in-depth look at the channel estimation and beamforming techniques jointly with their respective architectures for mm Wave massive MIMO system. In particular; sparse, compressed sensing, machine learning and array signal processing based channel estimation are addressed from 5G channel estimation techniques. On the other hand, beamforming techniques like hybrid beamforming and the low-complexity hybrid block diagonalization schemes with their mathematical analysis are included. This work also discusses in detail the challenges, optimization methods and mitigation techniques of pilot contamination, signal detection, channel estimation and hybrid beamforming for mm Wave massive MIMO system. The result asserts that partially connected block-diagonal hybrid bema forming with array signal processing based channel estimation is more optimal than the others

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with respect to over all performance, complexity and energy consumption. Finally, open research directions and challenges are pointed out.

Ismayil S. C. et al. [5], Massive MIMO is one of the cornerstones of 5G technology. MIMO scaled up to hundreds or even thousands of antenna terminals can result in an extensive increase in the capacity at reduced computational complexity. Channel State Information (CSI) estimation has an indispensable role in the deployment of massive MIMO. Since the spatial information is important for the massive MIMO phase component to have higher significance as compared to the magnitude component in CSI. If the phase estimation of the channel can be made accurate, we can ensure efficient estimation of channel gains as well. Thereby ensuring the error-free transmission of massive data. The proposed multi-layer perceptron model for massive MIMO takes the beamformed signal with higher directivity as its input and learns the features of different channel conditions and predict the direction of arrival (DoA) or Angle of Arrival (AoA) of the received signal. This accurate prediction of DoA helps in the estimation of channel conditions much better than the time domain counterpart especially with a reduced number of iterations. The proposed system has better metrics about the accuracy, mean squared error (MSE) performance, and bit error rate (BER) performance. The number of epochs required for training is less implies computational complexity is less, which is a significant improvement comparing with other data-driven techniques. Such a scheme that can make predictions on the channel at a very lesser time helps to adapt the transmission parameters according to the channel thereby ensuring in building a communication network that can handle the transmission of the huge volume of data that are free from any transmission errors or distortions.

Abboud, M. K. et al. [6], in this paper channel estimation techniques for a mobile fourth generation coherent Orthogonal Frequency Division Multiplexing (OFDM) system are proposed. Coherent detection dictates that a per-subband estimate of the frequency response of the channel is generated for each OFDM symbol. This is achieved by inserting pilot symbols amongst the data symbols in the OFDM modulation grid. With suitable interpolation, the channel estimate at all intermediate symbols can be generated. A number of channel estimation methods with different pilot patterns and interpolation methods are examined for a range of UTRA specified channel environments. Each environment is shown to have an optimal pilot scheme, power level, pattern and density and the paper proposes the use of adaptive pilot processing.

Siyad C. I. et al. [7], the physical layer security is a new security paradigm based on the principles of information theory. Several methods for achieving secrecy in physical layer is proposed. This paper proposes PLS based on the deep learning architecture. In which the deep learning model will transform the channel coefficients, the beamforming based on this transformed channel coefficients can be decoded using deep learning architecture in the receiver. The secrecy rate and secrecy outage probability of proposed system is compared with the zero forcing based beamforming and superior performance is verified by the simulation using popular deep learning library TensorFlow.

Malik P.K. et al. [8], Device to Device and Cooperative communication are the two new emerging technologies in the new era of communication technology which differ from the existing cellular technology. In review article we have enlisted different technologies which play a very important role in third Generation Partnership Project (3GPP). In this paper we have studied the various techniques of resource allocation, Mode selection for underlay communications in terms of device to device and cooperative communication techniques in terms of Long Term Evolution and Long Term Evolution-Advanced platform. A new technique LTE-Advanced Pro has also been introduced by 3GPP. Various simulators including Vienna LTE-Advanced have also been discussed. Better utilization of the spectrum is also depicts which is done on the basis of analysis if proper resource allocation whether it is power, frequency or time and mode selection is done in the programmed manner which would result in the reduction of interference and it will also lead to the secure system.

IV. METHODOLOGY

The vast and accurate dataset is essential for the DL model in the data-driven mode, required for training, to evaluate the performance of the NN model. Remcom Wireless Insite provides the accurate ray-tracing scenarios dataset for different environmental conditions. The Deep MIMO dataset generation framework is utilized to construct the MIMO channels dataset. The original dataset is preferred. The data set is constructed using Deep MIMO, a Generic Deep Learning dataset for millimetre waves and Massive MIMO. It is easy to generate an accurate dataset using the framework.

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A Ray tracing scenario ultimately defines the deep MIMO dataset. It was generated by an accurate 3D ray-tracing simulator wireless Insite Remcom is free to download. Ray tracing scenarios help evaluate and compare the Machine learning and deep learning algorithms. Using DL, these huge datasets help to implement MIMO signal processing like channel estimation, mm-wave beam prediction, optimum power allocation, etc. The dataset generation has two essential steps

Step 1: Select the Ray-tracing Scenario accurately obtained from Remcom Wireless Insite. It describes the nature of the environment on which the channel gain depends.

Step 2: Parameter setting for selecting the number of BS, UEs and multipaths, system bandwidth, OFDM parameters, etc.

Fig 3 shows the process of Deep MIMO dataset generation.

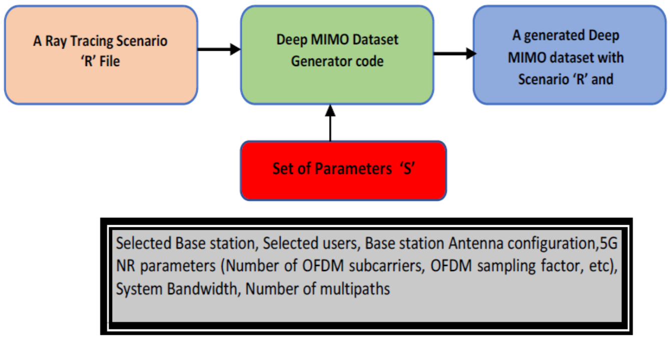

Figure 3: ML MIMO dataset generation framework

The generated dataset contains the channel gain matrix H and user location. The channel coefficients are complex and cannot be used as it is directly. The Deep Neural Network uses the labelled training and testing data, which must be real form. Thus, the pre-processing of a generated dataset is a must. Complex channel coefficients that use the maximum absolute channel value of the dataset are normalized within the range [-1 1]. The pilot symbols $\emptyset$ of length P are generated from UE and combined with the channel Coefficient matrix H. The noise w is added to the receiver. These received signals y with corresponding channel matrix H act as training data and labels. As a single UE is assumed, after Vectorizing, the received has dimension MPx1. The Channel matrix-vector and measured received vectors are separated into real and imaginary parts and then flattened to (2Mx1) and (2MP) vectors. This 70% of the processed dataset is considered for training, and the remaining 30% for testing the DL-FCNN for channel estimation.

4.1 IOT Application

Smart Home: With IoT creating the buzz, 'Smart Home' is the most searched IoT associated feature on Google. But, what is a Smart Home? Wouldn't you love if you could switch on air conditioning before reaching home or switch off lights even after you have left home? Or unlock the doors to friends for temporary access even when you are not at home. Don't be surprised with IoT taking shape companies are building products to make your life simpler and convenient. Smart Home has become the revolutionary ladder of success in the residential spaces and it is predicted Smart homes will become as common as smartphones. The cost of owning a house is the biggest expense in a homeowner's life. Smart Home products are promised to save time, energy and money.

Wearables:- Wearables have experienced a explosive demand in markets all over the world. Companies like Google, Samsung have invested heavily in building such devices. But, how do they work?

Wearable devices are installed with sensors and software which collect data and information about the users. This data is later pre-processed to extract essential insights about user.

Connected Cars: The automotive digital technology has focused on optimizing vehicles internal functions. But now, this attention is growing towards enhancing the in-car experience.

A connected car is a vehicle which is able to optimize its own operation, maintenance as well as comfort of passengers using onboard sensors and internet connectivity.

Most large auto makers as well as some brave startups are working on connected car solutions. Major brands like Tesla, BMW, Apple, and Google are working on bringing the next revolution in automobiles.

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Industrial Internet: Industrial Internet is the new buzz in the industrial sector, also termed as Industrial Internet of Things (IOT). It is empowering industrial engineering with sensors, software and big data analytics to create brilliant machines. According to Jeff Immelt, CEO, GE Electric, IOT is a "beautiful, desirable and investable" asset. The driving philosophy behind IOT is that, smart machines are more accurate and consistent than humans in communicating through data. And, this data can help companies pick inefficiencies and problems sooner.
IOT holds great potential for quality control and sustainability. Applications for tracking goods, real time information exchange about inventory among suppliers and retailers and automated delivery will increase the supply chain efficiency. According to GE the improvement industry productivity will generate $10 trillion to $15 trillion in GDP worldwide over next 15 years.

Smart Cities: Smart city is another powerful application of IoT generating curiosity among world's population. Smart surveillance, automated transportation, smarter energy management systems, water distribution, urban security and environmental monitoring all are examples of internet of things applications for smart cities.
IoT will solve major problems faced by the people living in cities like pollution, traffic congestion and shortage of energy supplies etc. Products like cellular communication enabled Smart Belly trash will send alerts to municipal services when a bin needs to be emptied.
By installing sensors and using web applications, citizens can find free available parking slots across the city. Also, the sensors can detect meter tampering issues, general malfunctions and any installation issues in the electricity system. To understand better the functioning of Smart Cities check out this video.

V. CONCLUSION

The prime aim of the research work carried in the thesis is to propose an optimal hybrid beamforming technique for millimeter Wave massive MIMO systems with respect to spectral efficiency and computational complexity. The optimal hybrid beamforming technique is key enabler technology for future wireless communication systems. The future wireless communication systems are expected to completely revolutionize the user experience by providing the key services like device-to-device communication, augmented reality, autonomous vehicles, smart homes, smart cities, smart wearable devices, smart healthcare, machine-to-machine communication, smart agriculture and industrial IOT.

REFRENCES

[1] Farzana Kulsoom, Anna Vizziello, Hassan Nazeer Chaudhry and Pietro Savazzi, "Joint Sparse Channel Recovery With Quantized Feedback for Multi-User Massive MIMO Systems", IEEE Access 2020.

[2] Mustafa S. Aljumaily and Husheng Li, "Hybrid Beamforming for Multiuser MIMO mm Wave Systems Using Artificial Neural Networks", International Conference on Advanced Computer Applications, IEEE 2021.

[3] Osama I., Mohamed R., Mohamed E. and Sami E., "Deep Learning Based Hybrid Precoding Technique for Millimeter-Wave Massive MIMO Systems", IEEE International Conference on Electronic Engineering, IEEE 2021.

[4] T. Kebede, Y. Wondie and J. Steinbrunn, "Channel Estimation and Beamforming Techniques for mm Wave-Massive MIMO: Recent Trends, Challenges and Open Issues," 2021 International Symposium on Networks, Computers and Communications (ISNCC), pp. 1-8, 2021.

[5] Ismayil S. C., Tamilselvan S. and Sneha V. V, "Frequency Domain Learning Scheme for Massive MIMO Using Deep Neural Network", International Conference on Intelligent Computing and Control Systems (ICICCS), IEEE 2020.

[6] Abboud, M. K., &Sabbar, B. M," Performance evaluation of high mobility OFDM channel estimation techniques", International Journal of Electrical and Computer Engineering, Vol .10, no. 3, pp. 2562, June 2020.

[7] Siyad C. I. and Tamilselvan S., "Deep Learning Enabled Physical Layer Security to Combat Eavesdropping in Massive MIMO Networks", Lecture Notes on Data Engineering and Communications Technologies IEEE pp. 643-650,2020.

[8] Malik P.K., Wadhwa D. S. and Khinda J. S., "A Survey of Device to Device and Cooperative Communication for the Future Cellular Networks", International Journal Wireless Information Networks, IEEE 2020.

[9] H. Chen, J. Hua, J. Wen, K. Zhou, J. Li, D. Wang, and X. You, ''Uplink interference analysis of F-OFDM systems under non-ideal synchronization,'' IEEE Trans. Veh. Technol., vol. 69, no. 12, pp. 15500–15517, Dec. 2020.

[10] Ganesan Thiagarajan and Sanjeev Gurugopinath, "A Novel Hybrid Beamformer Design for Massive MIMO Systems in 5G", 3rd 5G World Forum (5GWF), IEEE PP. NO. 436-441, 2020.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

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| DOI: 10.15680/IJIRCCE.2024.1203066 |

[11] Chataut, R. and Akl, R.," Massive MIMO systems for 5G and beyond networks -overview, recent trends, challenges, and future research direction" , Sensors, Vol.20, no. 10, pp. 2753, 2020

[12] Al-Heety, A. T., Islam, M. T et al, "Performance Evaluation of Wireless data traffic in Mm wave massive MIMO communication," Indonesian Journal of Electrical Engineering and Computer Science, vol. 20, no. 3, pp. 1342-1350, 2020.

[13] S. Elhoushy and W. Hamouda, "Performance of Distributed Massive MIMO and Small-Cell Systems Under Hardware and Channel Impairments," in IEEE Transactions on Vehicular Technology, vol. 69, no. 8, pp. 8627-8642, Aug. 2020.

[14] X. Shao X. Chen and R. Jia "A dimension reduction-based joint activity detection and channel estimation algorithm for massive access" IEEE Trans. Signal Process. vol. 68 pp. 420-435 2020.

[15] L. Dai, R. Jiao, F. Adachi, H. V. Poor and L. Hanzo, "Deep Learning for Wireless Communications: An Emerging Interdisciplinary Paradigm," in IEEE Wireless Communications, vol. 27, no. 4, pp. 133-139, August 2020.

[16] Xin J., Zhong C. R. and Y. Li, "Antenna selection for multiple-input multiple-output systems based on deep convolutional neural networks", PLoS one, 14, 5, 1-16, 2019.

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