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A Selective Channel Estimation And Improvement Of The Performance In Ofdm Signal For 6g Communication

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Abstract- The sixth-generation (6G) wireless communication network is projected to incorporate the surface-dwelling, airborne, and naval communications into a strong network which would be more consistent, dissolute, and can provide a enormous number of devices with ultra-low potential requirements. Block chain, NOMA(non-orthogonal multiple access),quantum Machine learning(QML),edge Computing, small cells communication etc., are the highlighted technologies in the situation of beyond 5G(B5G) and 6G communication. Entire health sector will be dominated by 6G communication Technology in the upcoming era. Apart from health sectors diversified sectors are predominately occupy by 6G communication Technology. Perception of human Lifestyle are revolutionized by Artificial Intelligence based 6G communication Technology. In this paper Artificial Intelligent based 6G smart healthcare, haptic communication are briefly discussed. The key resistance of present healthcare system is time and space which is totally exhaust by implementing 6G communication technology interlinked with Internet of Things. Transportation of Patient from remote to Intensive care is facilitated by ambulance which can be serviced by normal vehicle also. Besides the hospitality for elderly peoples are very unsatisfactory most of them are died while transporting without having a proper communication. Real time date of a patient monitoring and accident detection system are lagging in the present scenario which is totally overcome by implementing AI-6G Integrated IoT based smart health care system.

Keywords- 6G communication, Haptic, Artificial Intelligence, Machine Learning

I. INTRODUCTION

The fifth generation (5G) wireless communication networks are being standardized and deployed worldwide from 2020. The three major communication scenarios of 5G are enhanced mobile broadband (eMBB), massive machine type communications (mMTC), and ultra-reliable and low latency communications (uRLLC). The key capabilities include 20 Gbps peak data rate, 0.1 Gbps user experienced data rate, 1 ms end-to-end latency, supporting 500 km/h mobility, 1 million devices/km2 connection density, 10 Mbps/m2 area traffic capacity, 3 times spectrum efficiency, and 100 times energy efficiency compared to the fourth generation (4G) wireless communication systems. Various key technologies such as the millimeter wave (mmWave), massive multiple-input multiple-output (MIMO), and ultra-dense network (UDN) have been proposed to achieve the goal of 5G [1]. However, 5G will not meet all requirements of the future in 2030+.

Researchers now start to focus on the sixth generation (6G) wireless communication networks. One of the main distinguishing features of 5G is low latency or more specifically guaranteed (deterministic) latency, which needs deterministic networking (DetNet) to guarantee end-to-end latency with punctuality and accuracy that future use cases demand. The 6G will have additional requirements of high time and phase synchronization accuracy beyond what 5G can deliver. Additionally, 6G will have to provide near 100% geographical coverage, sub-centimeter geo-location accuracy and millisecond geo-location update rate to meet use cases. As 5G networks are still limited to some typical scenarios, remote areas such as villages and motorways are not well covered, which limits some applications such as driverless vehicles. Non-terrestrial and specifically satellite communication networks are needed to complement the terrestrial networks for cost-effective, seamless, and ubiquitous service availability.

Unmanned aerial vehicle (UAV) communication network is important for fast response in harsh and difficult environments. Maritime communication network is needed to provide ships with high quality communication services. While mmWave can provide Gbps level transmission data rate in 5G, Tbps level transmission data rate will be needed for applications such as high quality three-dimensional (3D) video, virtual reality (VR), and mix of VR and augmented reality (AR), where teraherhz

(THz) and optical frequency bands can be candidate bands. Faced with the big datasets generated by using extremely heterogeneous networks, diverse communication scenarios, large numbers of antennas, wide bandwidths, and new service requirements, 6G networks will enable a new range of smart applications with the aid of artificial intelligence (AI) and machine learning (ML) technologies.

One automation level is for improving the network performance itself in many aspects, for example, quality of service (QoS), quality of experience (QoE), security, fault management, and energy efficiency. Up to 5G, traffic on the network is dominated by video or streaming applications. Besides all applications and requirements mentioned above, we can learn from 5G tactile Internet applications [2] that wireless networked control of robotic objects (as e.g., automated driving or factory logistics) is a new exciting application for cellular technology, but this also generates new challenges. When analyzing the network traffic generated by these applications, many mobile objects must share sensor as well as control information, which overburdens a centralized control system. Instead, distributed control systems using AI are becoming a focus in research and development.

In particular federated learning shows to be a promising approach, where dataset correlation algorithms are distributed over mobile robotic objects and aggregated learning happens over the cloud. Interestingly, this generates a completely new class of network traffic, with large bandwidth and widely varying latency demands. It is highly likely to assume that these and equivalent AI applications will not only overtake but dominate the network traffic demands of 6G. This is untouched soil, which makes it exciting and very challenging at the same time! In comparison with the 5G network, 6G wireless communication networks are expected to provide much higher spectral/energy/cost efficiency, higher data rate (Tbps), 10 times lower latency, 100 times higher connection density, more intelligence for full automation, sub-centimeter geo-location accuracy, near 100% coverage, and sub-millisecond time synchronization.

New air interface and transmission technologies are essential to achieve high spectrum efficiency and energy efficiency, including new waveforms, multiple access approaches, channel coding methods, multi-antenna technologies, and proper combination of all these diversity techniques. In the meanwhile, novel network architectures are needed, for example, software defined network/network functions virtualization (SDN/NFV), dynamic network slicing, service-based architecture (SBA), cognitive service architecture (CSA), and cell-free (CF) architectures. However, softwarization comes at a cost, as we can learn from 5G deployment. The use of commercial off-the-shelf (COTS) servers versus domain specific chips in a virtualized radio access network (RAN) implies a large increase in energy consumption, countering measures for improving energy efficiency. This results in the current fact that 5G networks consume more power than 4G networks, but of course at a delivery of a higher bandwidth. In contrast, we should deliver networks that at the time of their introduction do not exceed the previous generation's power needs. For 6G we therefore will require a new computing paradigm to support all benefits of softwarization without bearing the costs of energy consumption.

II. 6G-STANDARD

With 5G availability fast expanding worldwide and a "mid-generation" evolution cycle anticipated in 3GPP Release-18, now is the right time to lay down the foundations for the next generation, global 6G standard. MediaTek has played a leading role in the design, standardization and ongoing evolution of 5G. It has led the way in bringing to the market mature 5G devices that can operate in new groundbreaking 5G systems (i.e. both Radio and Core). As the world's leading smart phone chip supplier1 and an undisputed 5G commercial product leader, Media Tek is in a prime position to define and drive the vision and realization of next generation mobile technologies for 6G. 5G was engineered and has evolved around three core sets of use cases: enhanced mobile broadband (eMBB), ultra-reliable & low-latency communications (URLLC) and massive machine-type communications (mMTC). It has been purpose-built not only to embrace the mobile broadband revolution unleashed by 4G in the consumer space, but also to enable new growth opportunities beyond this market. Capitalizing on the foundations laid by 4G evolution into the cellular IoT market, 5G took a further, more significant leap to address the stringent requirements of industrial IoT.

5G has been conceived to bring the transformative power of mobile communications into every sector of our society; for the first time ever, a single communication system was designed not only to cater for a very diverse range of consumer and professional use cases in licensed and unlicensed spectrum, across sub-6 GHz and mmW bands, but also to provide connectivity beyond the traditional reach of terrestrial networks through airborne and satellite infrastructure that altogether integrates seamlessly. However, this ambitious design has translated into significant complexity for both networks and devices, leading to higher deployment costs and power consumption. As a result, the 5G rollout has been incremental, focusing mostly on eMBB consumer applications, in sub-6 GHz. Achieving ubiquitous mmW coverage has been a challenge, especially from network economic perspectives.

Further, while it is encouraging to see the rise of open RAN architecture coming together for 5G deployments to bring more flexibility and intelligence, the fundamental network design is still based on traditional mobile

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networks and layering. Significant enhancement will be expected to drive the architecture into the age of artificial intelligence and machine learning. While industry continues to evolve current 5G technology to address the aforementioned challenges, 6G technology is on the horizon to not only address these issues but also to bring fundamental transformation to mobile networks. Our 6G vision is of one global standardized technology to significantly outclass 5G and its evolution from the outset. 6G will deliver extreme performance using native adaptive radio and networking technologies that can support consumer and professional markets with diverse data consumption models, in a fully secure and sustainable manner.

III. 6G COMPUTING TECHNOLOGIES

Computing technologies such as the cloud computing, fog computing, and edge computing are important for network resilience, distributed computing and processing, and lower latency and time synchronization. In order to solve the limitations of 5G including the drawback of short-packet, provide the delivery of high-reliability, low-latency services with high data rates, system coverage and Internet of everything (IoE) [3], and to meet the demands of mobile communications of the year 2030 and beyond [4], 6G network should make the human-centric, instead of machine-centric, application-centric, or data-centric, as the vision [5]. To meet these requirements, 6G wireless communication networks will have new paradigm shifts. Our vision of 6G network is illustrated in Fig. 1. First of all, 6G wireless communication networks will be space-air-ground-sea integrated networks to provide a complete global coverage.

The satellite communication, UAV communication, and maritime communication will largely extend the coverage range of wireless communication networks. To provide a higher data rate, all spectra will be fully explored, including sub-6 GHz, mmWave, THz, and optical frequency bands. To enable full applications, AI and ML technologies will be efficiently combined with 6G wireless communication networks to have a better network management and automation.

Furthermore, AI technology can enable the dynamic orchestration of networking, caching, and computing resources to improve the performance of next-generation networks. The last but not the least trend is the strong or endogenous network security for both physical layer and network layer when developing it. Industry verticals, such as cloud VR, Internet of things (IoT) industry automation, cellular vehicle to everything (C-V2X), digital twin body area network, and energy efficient wireless network control and federated learning systems will largely boost the developments of 6G wireless communication networks. An overview of 6G wireless networks is shown in Fig. 1, where the performance metrics, application scenarios, enabling technologies, new paradigm shifts, and industry verticals are given.

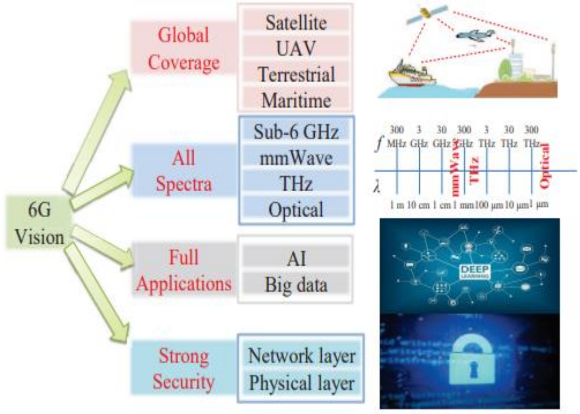

Fig. 1. A vision of 6G wireless communication networks.

IV. PERFORMANCE METRICS, APPLICATION SCENARIOS, AND EXAMPLE INDUSTRY VERTICALS

Performance Metrics and Application Scenarios Compared to 5G (IMT-2020) [6], 6G networks are expected to achieve superior performance and have more performance metrics, as illustrated in Fig. 1.. The peak data rate for 5G is 20 Gbps, while for 6G networks it can be 1–10 Tbps with the aid of THz and optical frequency bands. The user experienced data rate can achieve a Gbps-level with these high frequency bands.

The area traffic capacity can be more than 1 Gbps/m2 . The spectrum efficiency can increase 3–5 times, while the network energy efficiency must increase by more than 100 times compared to 5G to make-up for the increase in data rate by 100 times. This can be achievable by applying AI to achieve much better network management and automation. The connection density will increase 10–100 times due to the use of extremely heterogeneous networks, diverse communication scenarios, large numbers of antennas, and wide bandwidths. There are multiple types of mobility introduced by satellites, UAVs, and ultra-high-speed trains, which can move with a much higher speed of larger than 500 km/h in comparison to the existing terrestrial terminals. For a selected set of applications, the latency is expected to be less than 1 ms. In addition, other important performance metrics should be introduced, e.g., cost efficiency, security capacity, coverage, intelligence level, etc [7].

V. MULTIPLE ACCESSES

Multiple access techniques define how bandwidth resources are shared among mobile users and have been recognized as key milestones for the migration of cellular networks [4,5]. For the past generations of mobile networks, orthogonal multiple access (OMA) has been used, where orthogonal bandwidth resource blocks are first generated in the time, frequency, or code domains (e.g., time slots, sub-carriers, and spreading codes), and then allocated to users in an orthogonal manner, i.e., one resource block is solely occupied by a single user. The success of OMA in the past-generation mobile networks is mainly due to the fact that it can be implemented in a low complexity way, although it has been known since Shannon's work on multiple access channels that the spectrum efficiency of OMA is sub-optimal [6]. Non-orthogonal multiple access (NOMA) is a paradigm shift for the design of next-generation multiple access techniques. The key idea of NOMA is to encourage the spectrum sharing among mobile users, where the superior spectral efficiency gain of NOMA over OMA is obtained by opportunistically utilizing the users' dynamic channel conditions or heterogeneous QoS requirements [7].

Take the power-domain NOMA as an example [8]. Multiple users with different channel conditions are served at the same time, frequency, and spreading code. As such, NOMA avoids spectrally inefficient situation in which valuable bandwidth blocks are solely occupied by users whose channel conditions are poor. Sophisticated multiuser detection techniques are used by NOMA to ensure that multi-access interference due to spectrum sharing is effectively suppressed with reasonable computational complexity. NOMA was originally developed for 5G mobile systems, where its superior spectral efficiency has been demonstrated by extensive theoretic studies as well as experimental trials carried out by academia and industry.

However, the vision that NOMA should replace OFDM in 5G systems was not fulfilled. Instead, NOMA was used as an optional transmission model for downlink transmission. We note that this setback for the NOMA standardization progress is not because there were no enough interests in NOMA. Despite of the huge interests from industry and academia, there are still some technical reasons and arguments which cause the difficulty for the standardization of NOMA.

Take multi-user superposition transmission (MUST) as an example, which is a study item in 3GPP Release 14 to use NOMA for downlink transmission [9]. There were 15 proposals by different industrial companies. Such divergence resulted in a compromised situation, where MUST was included in 3GPP Release 15 as an optional mode only [10]. Another example is NOMA, which is a study item in 3GPP Release 16 to use NOMA for uplink transmission. With more than 20 different forms proposed to NOMA, the 3GPP working group could not reach consensus, which resulted in the fact that NOMA was not included in 5G NR [11]. Therefore, an important lesson from the standardization of 5G-NOMA is to avoid divergence, which means that the convergence is the top priority to develop a unified framework of 6G-NOMA.

• From the technical perspective: Such a unified NOMA framework should retain the superior performance promised by different 5G-NOMA forms, e.g., supporting massive connectivity, realizing excellent user fairness, striking a balanced tradeoff between energy and spectral efficiency, etc. It is worth pointing out that most existing 5G-NOMA forms have been developed for particular purposes. For example, sparse code multiple access (SCMA) was developed primarily to support massive connectivity for mMTC, whereas power-domain NOMA is well known for its ability to increase the system throughput for eMBB [12]. Therefore, a general framework is crucial for the deployment of NOMA in 6G systems, where sophisticated tools, such as multi-objective optimization and multi-task learning, will be useful to establish such a framework.

From the practical implementation perspective: The unified NOMA framework needs to be robust against dynamic wireless propagation environments and users' complex mobility profiles. To realize a robust NOMA transmission, instead of relying on users' instantaneous channel conditions which can be rapidly changing in practice, the use of users' heterogenousQoS requirements could be more reliable in practice [3], since users' QoS requirements are changing in a much slow manner. In particular, users with low QoS requirements can be grouped with users with demanding QoS requirements for spectrum sharing, which can significantly improve spectral efficiency. When there are users with heterogenous mobility profiles in the system, the use of the delay-Doppler plane has been shown to yield more degrees of freedom for the system design, compared to the use of the conventional time-frequency plane [4, 5].

VI. PROPOSED METHODOLOGY NEXT GENERATION MULTIPLE ACCESS (NGMA)

AI Enabled NOMA Towards NGMA Despite the promise of NGMA, the complicated multidomain multiplexing also makes the interference suppression and the system optimization increasingly challenging. Particularly, the communication design of next generation NOMA systems typically leads to a highly complex nonconvex mixed-integer nonlinear programming (MINLP) problem, whose globally optimal solution is extremely difficult to obtain. While conventional convex optimization methods can achieve the local optimum, they usually encounter several critical challenges in practice:

(i) They rely on sophisticated mathematical transformations and expert experiences to transfer original non-convex problems into tractable convex problems.

(ii) The resulting performance is severely sensitive to initialized parameters, which should be appropriately

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configured for different scenarios via laborious hand-engineered designs.

(iii) They often require large amounts of iterations to reach convergence, leading to an impractically high computational complexity especially in the overloaded regime or multi-cell networks.

Fortunately, recent advances in AI have created new opportunities to circumvent the above challenges, which enables the automated communication designs to combat the overwhelming system complexity and heavy dependence on human interventions [4]–[7]. In this article, we explore promising and advanced machine learning (ML) methods to empower NGMA via AI. While existing research contributions have laid a solid foundation on multiple-antenna NOMA communication designs, AI enabled NGMA is still in its infancy, which motivates us to develop this treatise. The main contributions of this article can be summarized as follows.

Generalize the existing multiple-antenna NOMA schemes, thus enabling a new scenario-adaptive communication paradigm towards NGMA.

- We investigate promising machine learning methods and highlight their features and application scopes, which can autonomously learn high-efficiency communication designs with computationally realizable complexity and fewer human interventions.
- We propose two machine learning paradigms, which enables efficient SIC and beamforming design in singlecell and multi-cell networks by extending conventional deep reinforcement learning (DRL) and graph neural network (GNN), respectively.

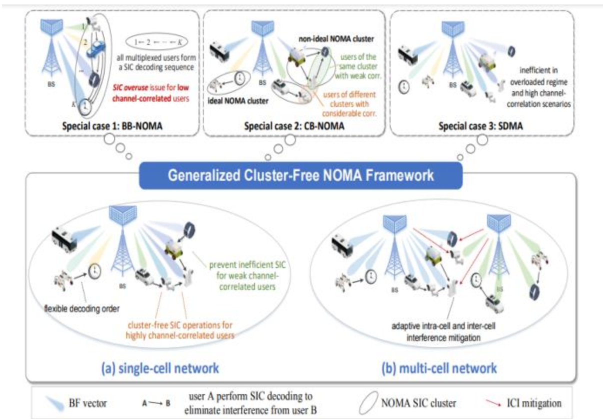

Fig. 2: Illustration of the proposed generalized cluster-free NOMA framework in single-cell and multi-cell networks.

VII.AI ENABLED NOMA FRAMEWORK FOR NGMA

In this section, we first propose a novel generalized cluster free multiple-antenna NOMA framework to achieve scenario adaptive communications towards NGMA. Then, to cope with the overwhelming complexity of next generation wireless systems, we further investigate promising AI enabled methods to achieve automated, computationally realizable, and efficient communication design.

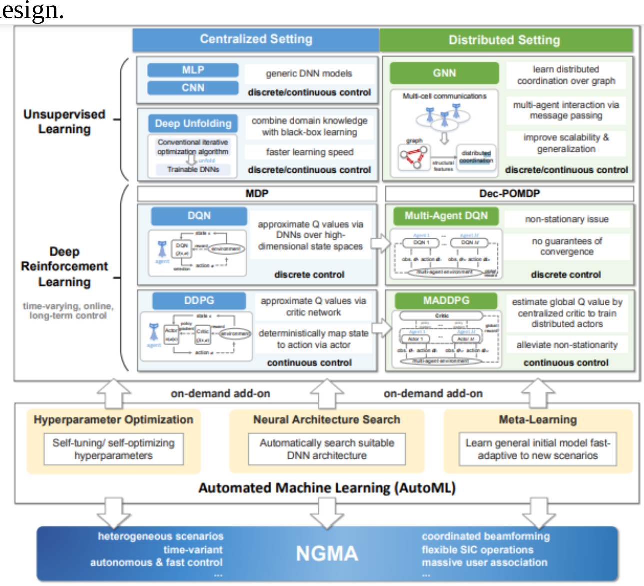

Fig. 3: Overview of AI enabled NGMA.

1.Cluster-Free Noma Framework For Ngma

As shown propose a novel downlink cluster free NOMA framework, which can be employed in both the single-cell and multi-cell networks. Without loss of generality, we suppose that the base station (BS) is equipped with multiple antennas to serve multiple single-antenna users. Note that the proposed framework can be applied to both under loaded and overloaded regimes. To achieve fully spatial multiplexing, each user in our proposed framework is served by a dedicated beamforming vector. Different from conventional multiple antenna NOMA schemes that require sequentially performing SIC within predefined user clusters, the proposed framework completely eliminates the restriction of clusters and allows flexible SIC operations between users. Specifically, the control of cluster-free SIC operation can be determined by a binary indicator, which decides whether a user will decode the signal of another user before decoding its own signal for interference elimination. Note that to ensure successful SIC decoding, the SIC decoding condition should be guaranteed [8]. The benefits of the proposed cluster-free NOMA are twofold.

2. Generalization

The proposed cluster-free NOMA provides a general framework. Specifically, it is equivalent to spatial-division multiple access (SDMA) SDMA/BB-NOMA when SIC operations are prevented/performed among all users. Moreover, it reduces to CBNOMA when SIC can be only sequentially carried out within predefined user clusters. Therefore, the current SDMA, BBNOMA, and CB-NOMA schemes that are suitable for specific scenarios can be considered as special cases of the proposed framework.

3.Ultra-flexible SIC successive interference cancellation (SIC):

The proposed cluster-free NOMA provides an ultra-flexible SIC design. It can adaptively prevent inefficient SIC among any users with weak channel correlations, thus avoiding system performance degradation caused by unfavourable SIC decoding conditions. Meanwhile, it allows SIC between any highly channel correlated users to achieve flexible interference elimination without cluster limitations. As a result, the proposed framework can enhance system performance and enable a novel scenario-adaptive multiple-antenna NOMA paradigm towards NGMA.

4.Promising Machine Learning Solutions For Ngma

Due to the increasing complexity of next generation wireless systems, the communication design typically needs to solve challenging high-complexity, coupled, and non-convex MINLP problems. To circumvent the inefficiencies of conventional convex optimization methods for NGMA, we investigate promising machine learning solutions in this part. Relying on the outstanding ability of deep models to fit any arbitrary function, AI can train deep neural networks (DNNs) to approximate the optimal solutions of challenging optimization problems. Specifically, the optimal solutions can be regarded as a non-convex function that maps the system state to the optimization variables.

AI can automatically learn high-quality solutions for communication designs in a data driven manner, which avoids the dependence on expert knowledge and the hand-engineered parameter initialization required by conventional optimization methods. Moreover, since DNNs only require lightweight computations during the forward propagation, learning-based solutions can significantly reduce the computational complexity to achieve fast time response and automated control in realistic environments. Since supervised learning requires massive data samples labelled with high-quality solutions, it has limited applicability for complex optimization problems. Hence, we focus on prospective unsupervised learning and DRL based solutions, and also investigate the emerging automated machine learning (AutoML) methods.

An overview of AI enabled NGMA can be illustrated, and the comparisons of representative machine learning algorithms are summarized. Unsupervised learning: While supervised learning aims to approximate the pre-labelled solutions, unsupervised learning can train the model parameters by directly minimizing unsupervised loss function without knowing ground-truth labels. Two generic machine learning models commonly employed in wireless communications are multi-layer perceptron (MLP) and convolutional neural network (CNN) [5]. However, since these models are inherently black-box and originally developed to accomplish computer vision tasks, they generally lead to degraded performance when being employed in wireless communications. To tailor unsupervised learning for wireless communications and circumvent these drawbacks, the following two approaches have been proposed.

5.Deep unfolding

Deep unfolding provides a new learning paradigm to incorporate domain knowledge and optimization theory into learning [6]. The core idea is to unfold the iterative optimization algorithm as the layer-wise learning model. By approximating the iterative pattern of optimization, black-box DNNs can be transformed into trainable white-box models with both theoretically interpretability and learning capability. Hence, enhanced performance can be achieved while reducing the number of training parameters and accelerating the convergence.

6.Graph neural networks (GNNs):

Compared to conventional non-structural DNNs, GNNs propose a structural learning paradigm to model the interplay effects and unveil the underlying dependencies among wireless nodes [7]. Based on GNNs, the structural features over graph can be learned via message passing to enable distributed inference. Therefore, GNNs can significantly improve scalability and generalization ability of unsupervised learning, thus realizing efficient coordination in distributed wireless communication designs

VII. RESULT AND SIMULATION

Examined neural network (NN) for combined channel estimation and signal detection in an OFDM system. This approach considered OFDM system and fading channel as a black box and the presented NN network is trained offline using simulated data. The simulation results revealed that the proposed DL approach had the capability to learn and investigate the complicated attributes of the wireless channels. In addition, the results of the DL approach proved its dominance over conventional methods when fewer pilot symbols were utilized, and cyclic prefix was ignored.

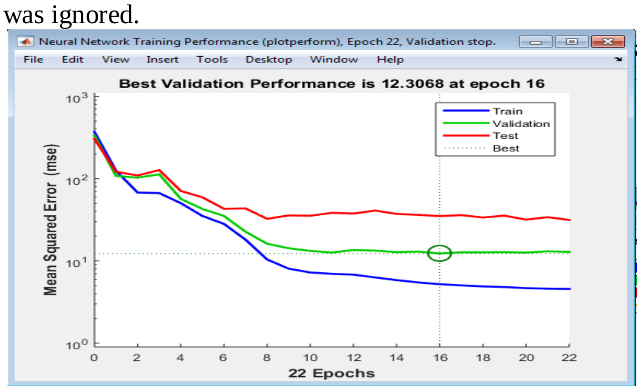

Fig.4 BER in NOMA.

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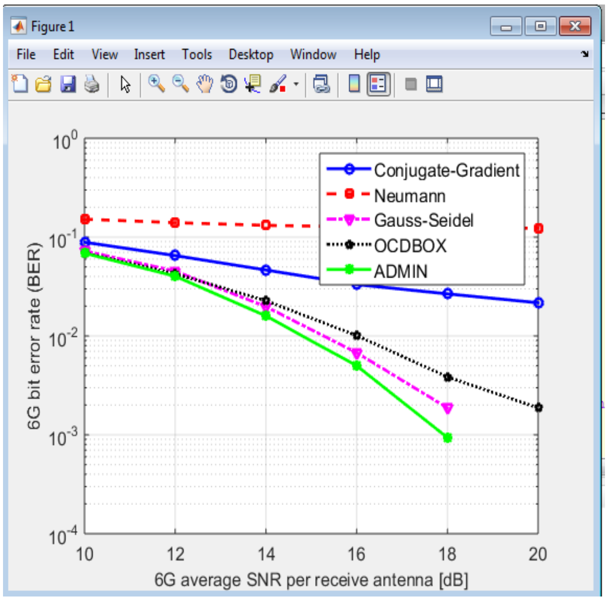

Fig.5 Regression.

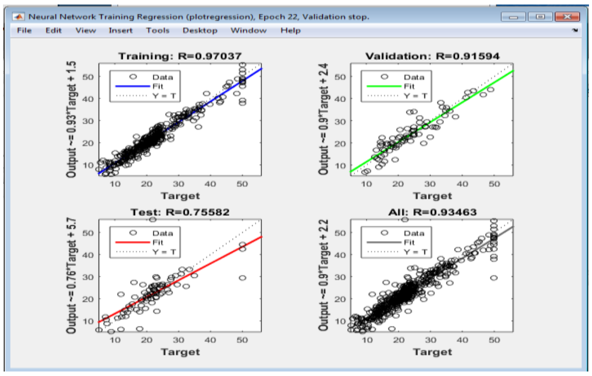

Fig.6 MSE.

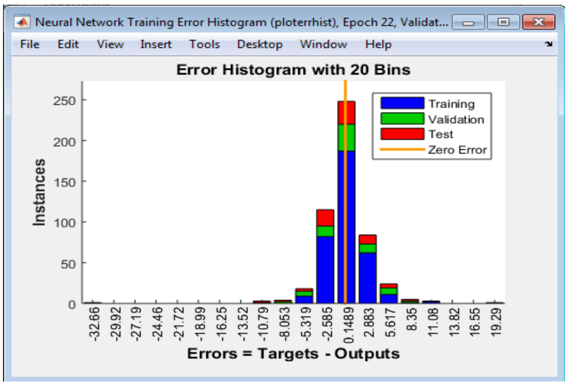

Fig.7 Performance plot.

VIII. CONCLUSION AND FUTURE SCOPE

Conclusion

The application of deep learning in MIMO-NOMA communication systems is a promising approach to address the shortcomings of the SIC method. Instead of the complicated algorithm design and interference cancellation process, the deep learning approach can search for the optimal solution of the hyper parameters of the multilayer neural network with machine learning. In this work, we designed an MIMO-NOMA-DL signal-detection system to perform signal recovery. The proposed technique can simultaneously complete the processes of channel estimation and MIMO-NOMA signal detection. The detailed construction and learning algorithm have been provided. We first compared the SER performance of the proposed method and the SIC algorithm via simulations. The highest performance gain reached 3.6 dB. Then, the impact of the crucial parameters, including the modulation type and power allocation, were studied. Numerical results showed that the MIMO-NOMA-DL method had powerful detection performance. Finally, mini-batch gradient descent simulations were conducted to accelerate the training step of the MIMO-NOMA-DL algorithm. The results indicate that the mini-batch size is a key parameter for balancing the convergence speed and loss precision.

REFERENCES

1. Ahammed, T. B., Patgiri, R., &Nayak, S. (2023). A vision on the artificial intelligence for 6G communication. ICT Express, 9(2), 197-210.
2. Jain, P., Gupta, A., & Kumar, N. (2022). A vision towards integrated 6G communication networks: Promising technologies, architecture, and use-cases. Physical Communication, 55, 101917.
3. Banafaa, M., Shayea, I., Din, J., Azmi, M. H., Alashbi, A., Daradkeh, Y. I., &Alhammadi, A. (2023). 6G mobile communication technology: Requirements, targets, applications, challenges, advantages, and opportunities. Alexandria Engineering Journal, 64, 245-274.
4. Wei, Z., Wang, Z., Zhang, J., Li, Q., Zhang, J., & Fu, H. Y. (2022). Evolution of optical wireless communication for B5G/6G. Progress in Quantum Electronics, 83, 100398.
5. Wang, C., Yu, X., Xu, L., Wang, Z., & Wang, W. (2023). Multimodal semantic communication accelerated bidirectional caching for 6G MEC. Future Generation Computer Systems, 140, 225-237.
6. Suriya, M. (2022). Machine learning and quantum computing for 5G/6G communication networks-A survey. International Journal of Intelligent Networks.
7. Hajiyat, Z. R., Ismail, A., Sali, A., &Hamidon, M. N. (2021). Antenna in 6G wireless communication system: Specifications, challenges, and research directions. Optik, 231, 166415.
8. Saxena, G., Chintakindi, S., Kasim, M. A., Maduri, P. K., Awasthi, Y. K., Kumar, S., ... & Dewan, C. (2022). Metasurface inspired wideband high isolation THz MIMO antenna for nano communication including 6G applications and liquid sensors. Nano Communication Networks, 34, 100421.

9.Muheidat, F., Dajani, K., &Lo'ai, A. T. (2022). Security concerns for 5G/6G mobile network technology and quantum communication. Procedia Computer Science, 203, 32-40.
10.Kumar, L. J. S., Krishnan, P., Shreya, B., &Sudhakar, M. S. (2022). Performance enhancement of FSO communication system using machine learning for 5G/6G and IoT applications. Optik, 252, 168430.
11.Sheth, K., Patel, K., Shah, H., Tanwar, S., Gupta, R., & Kumar, N. (2020). A taxonomy of AI techniques for 6G communication networks. Computer communications, 161, 279-303.
12.Ioannou, I., Christophorou, C., Vassiliou, V., &Pitsillides, A. (2022). A novel Distributed AI framework with ML for D2D communication in 5G/6G networks. Computer Networks, 211, 108987.