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Optimization For Sub Chanel and Power Allocation 5 G / 6G Wireless Communication Systems using Machine Learning

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Abstract: For several decades, optimization has been a key component in solving issues with wireless resource management, including beamformer design and power control. But these algorithms frequently need a large number of iterations to converge, which presents problems for real-time processing in systems like 5G/6G. We present a novel learning-based strategy for wireless resource management in this work. The main concept is to approximate the input and output of a resource allocation algorithm unknown non-linear mapping using a deep neural network (DNN). In order to create DNNs that can approximate certain algorithms of interest in wireless communications, we first characterize a class of `learnable algorithms' in this study. We show through extensive numerical simulations that DNNs can better approximate two extremely complicated algorithms used in wireless transmit signal design for power allocation while providing orders of magnitude computational time savings.

Keywords: Power Control, Beamformer Design , Transmit Signal, Computational Time, Magnitude Speedup.

1. Introduction

In the 1980s, the first generation (1G) of commercial cellular networks went live, including rudimentary phone services. Ten years later, 2G cellular networks took the place of 1G networks, offering increased capacity and digital voice communications services. Specifically, code division multiple access (also known as CDMA) or time division multiple access (TDMA) are used to provide the greater rates that 2G systems offer. These 3G networks made it feasible for mobile devices to access the Internet, which provides a variety of services like online TV, file transfers, and video calls. The ITU-R released the fourth generation (4G) criteria in 2008. For high-mobility and low-mobility communications, respectively, service speeds of 100 Mbps and 1Gbps are required. As 4G networks were being deployed globally by 2011, 4G standards had been completed. The next generation of wireless networks, known as fifth-generation (5G), is anticipated to launch after 2020 due to the ten-year cycle for each generation.

Specifically, the two 4G technologies that are being proposed: Worldwide Interoperability for Microwave Access (WiMAX) and Long-Term Evolution (LTE). The sixth generation of wireless communication technology, or 6G, is what comes after 5G. In comparison to its predecessors, it is anticipated to offer significantly faster data rates, reduced latency, increased dependability, and increased capacity. These techniques have a substantial computational overhead, which makes real-time implementation difficult because they are generally executed in a time of milliseconds. This paper is organized as , Section 1 contains the introduction of communication systems, Section 2 contain the literature survey of optimization for subchannel and power allocation, Section 3 contain some measures of proposed work, section 4 explains about the results of the project ,section 5 concludes the researched work and discuss about the future directions.

1.1. Resource Allocation in 5G/6G

Massive MIMO (Multiple Input Multiple Output): Building upon the advancements of MIMO in 5G, 6G is likely to employ even larger antenna arrays, enabling higher spectral efficiency and better coverage.

Artificial Intelligence (AI) Integration: AI and machine learning will play a significant role in optimizing network performance, managing resources, and enabling intelligent communication protocol in 6G networks.

1.2. Neural Networks

Work on artificial neural networks, commonly referred to as “neural networks”. It has the capability to organize its

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structural constituents, known as neurons, so as to perform certain computations. A neuron is composed of three main components: the dendrites, the cell body, and the axon.

These models could adapt to changing communication environments in real-time, offering improved performance and reliability. Additionally, neuromorphic hardware is expected to be more energy-efficient compared to traditional digital signal processing approaches, which could be beneficial for 6G systems that will likely have stringent energy requirements.

2. Related Works

2.1. Literature Survey

"Deep Learning for RA in Wireless Networks: A Survey" by Zeng et al. (2021), This survey paper provides a comprehensive overview of the application of deep learning in resource allocation for wireless networks. The authors discuss various deep learning models, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep reinforcement learning (DRL), and their applications in resource allocation tasks, such as channel allocation, power allocation, and user association.

"Resource Allocation in 6G Networks using DL: A Review" by Kumar et al. (2020): This review paper focuses specifically on the use of deep learning for resource allocation in 6G networks. The authors provide a detailed analysis of various deep learning models, including supervised, unsupervised, and reinforcement learning, and their applications in resource allocation.

"Deep Reinforcement Learning for Resource Allocation in Wireless Networks: A Tutorial"by Liu et al. (2019): This tutorial paper provides an in-depth introduction to the use of deep reinforcement learning (DRL) for resource allocation in wireless networks, including 6G systems. The authors discuss the basics of DRL, its application in resource allocation tasks, and its advantages over traditional approaches.

"Machine Learning for Resource Allocation in 6G Networks: Potentials, Applications, and Challenges" by Jiang et al. (2018): This paper provides a comprehensive overview of the potential applications of machine learning, including deep learning, for resource allocation in 6G networks. The authors discuss various resource allocation tasks, such as spectrum allocation.

2.2. Experimental Procedure

Traditional optimization techniques and their limitations. Challenges and requirements unique to 6G networks influencing subchannel and power allocation. In-depth exploration of various deep learning models and algorithms. Comparative analysis of deep learning approaches with conventional methods. Performance metrics used for evaluating optimization technique.

3. Results and Discussion

3.1. DNN Sample Performance

Without more information about the specific communication system that is being studied , it is difficult to say for sure why DNN has a better sum rate in this case.

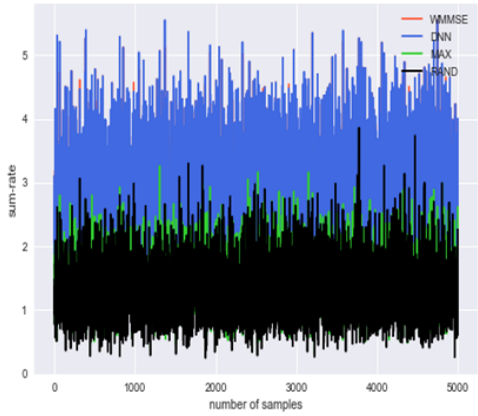

Figure. 1 DNN sample performance for k= 10 users

3.2. DNN Sum rate Distribution

The below figure shows that the number of samples collected for different scenarios. The x-axis represents the sum-rate , which is likely referring to the total data rate achieved in a communication channel . The y-axis represents the number of samples. The graph suggests that using a Deep Neural Network (DNN) leads to a higher data rate compared to the three other scenarios tested in this case

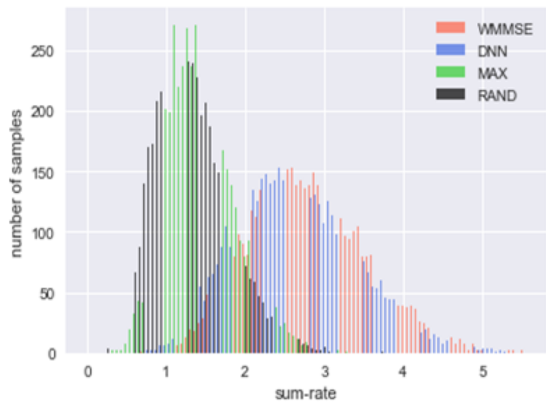

Figure. 2 Sum Rate Distribution for K=10 users

The x-axis of the above figure is labelled "number of samples" and the y-axis is labelled "sum-rate." The four lines in the figure represent different algorithms: WMMSE, CNN, MAX, and RAND. The

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WMMSE line appears to have the highest sum-rate for all numbers of samples.

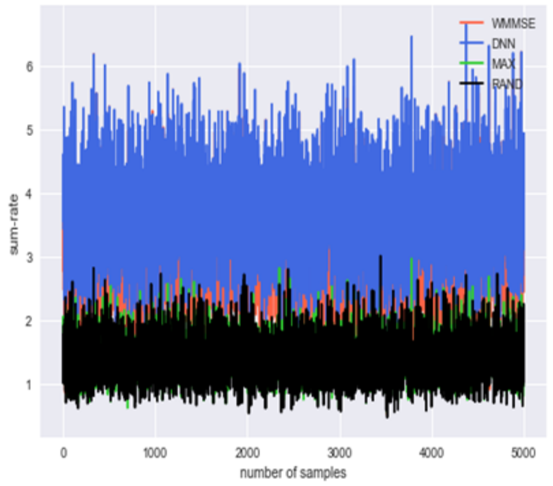

Figure. 3 DNN Sample Performance for k =20 Users

Computation Time

The computation time for all algorithms, including DNN, is likely to increase as the number of users grows. This was evident from the table where computation time went up for all three methods (WMMSE, DNN, Maximum Power Allocation) with more users.

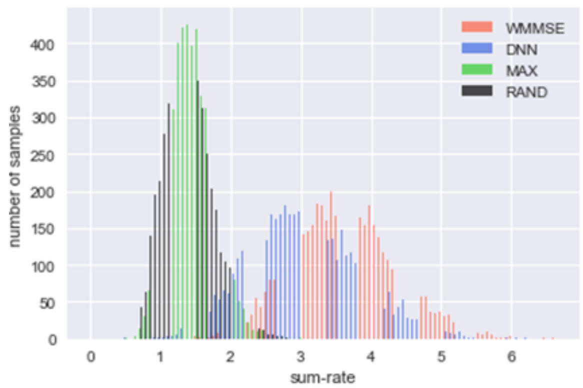

Figure. 4 DNN Sum Rate Distribution for K = 20 Users

The sum rate achieved by DNN (Deep Neural Network) might see a decrease compared to lower user loads. It shows a reduction in DNN's performance gain with increasing users. By using DNN , it shows the sumrate is increased. lower user loads. It shows a reduction in DNN's performance gain with increasing users.

The x-axis represents the sum-rate , which is likely referring to the total data rate achieved in a communication channel. The y-axis represents the number of samples. There are four lines in the graph, labelled WMMSE, DNN, MAX and RAND. It appears that DNN achieves the highest sum-rate among the four scenarios. Here's a possible explanation for each WMMSE could refer to Minimum Mean Square Error , which is an estimation technique used in signal processing.

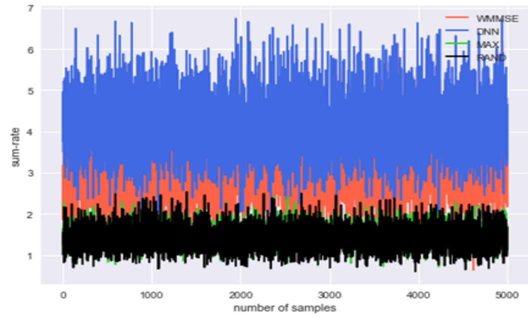

Figure. 5 DNN Sample performance for k = 30 Users

Power Allocation:

Power allocation is the process of assigning power to different subchannels. This is important because different users may have different requirements for data rate and quality of service

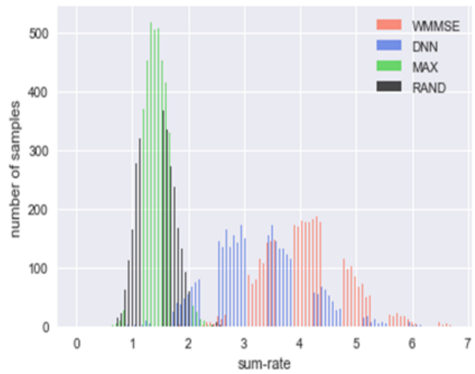

Figure. 6 DNN Sum Rate Distribution for K = 30 Users

Table. 1 Performance Comparison for Computation Time

	K = 10 Users		K = 20 Users		K= 30 Users	
	Computation time	Performance improvement	Computation time	Performance improvement	Computation time	Performance improvement
WMMSE ALGORITHM	14.101s	NA	49.388s	NA	80.691 s	NA
DEEP NEURAL NETWORK	0.110 s	128.2 times	0.170 s	289.9 times	0.230s	350.9 times
MAXIMUM POWER	0.110 s	128.2 times	0.170 s	289.9 times	0.230 s	350.9 times
RANDOM POWER	0.110 s	128.2 times	0.170 s	289.9 times	0.230 s	350.9 times

The improvement in computation time achieved by DNN compared to the baseline increases as the number of users increases.

Overall, the table suggests that a Deep Neural Network (DNN) based approach is the most efficient method in terms of computation time for this communication system The table compares the performance at three different user loads: K-10 users, K-20 users and K = 30 users.

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For each user load, the table shows the sum rate achieved by each algorithm and the improvement over a baseline that is not shown in the table. DNN has the lowest computation time compared to WMMSE and Maximum Power Allocation for all three user loads.

Table. 2 Performance Comparison (Sum Rate Performance)

	K = 10 Users		K = 20 Users		K= 30 Users	
	Sumrate In bps	Performance improvement	Sumrate In bps	Performance improvem ent	Sumrate In bps	Performance improvement
Wmmse Algorithm	2.818 bps	NA	3.631 bps	NA	4.145 bps	NA
Deep Neural Network	2.650 bps	94.027 %	3.049 bps	83.963 %	3.244 bps	78.761 %
Maximum Power	1.423 bps	50.502 %	1.438 bps	39.596 %	1.445 bps	34.874 %
Random Power	1.309 bps	46.461 %	1.385 bps	38.141 %	1.410 bps	34.021 %

The above table shows a performance comparison of different computation methods for a communication system. The table compares three algorithms: WMMSE, Deep Neural Network (DNN), and Maximum Power Allocation. The performance is measured in computation time (seconds) and improvement over a baseline that is not shown in the table.

The table shows the average computation time for three different user loads: K=10 users K = 20 users and K=30 users.

Table. 3 Comparison of Sum rate performance improvement for various users

Number of Users	DNN Surmate	WMMSE Surmate	%Improvement (DNN)
K = 10	2.670	2.817	94.78%
K = 20	3.143	3.424	91.79%
K = 30	3.582	4.123	86.87%

Table. 4 Comparison of Computation time improvement for various users

Number of Users	DNN Surmate	WMMSE Surmate	X Improvement (DNN)
K = 10	0.050	4.40	88.0 X
K = 20	0.293	59.41	202.7X
K = 30	0.149	122.91	824.89X

Above tables are the performance resulsts of WMMSE and DNN. Where the sum rate imporvement and computation time for various users has been tabulated as below.

The above table shows that it compares the sum rate performance improvement of a Deep Neural Network (DNN) based approach to a WMMSE approach for different numbers of users (K).

The improvement in Sum rate achieved by DNN compared to the baseline increases as the number of users increases. . It shows a reduction in DNN's performance gain with increasing users. By using DNN , it shows the sum rate is increased. lower user loads.

Equation / Formula

- The signal to interference-plus-noise ratio (SINR) for each receiver k is given by

$$\text{sinr}_k \triangleq \frac{|h_{kk}|^2 p_k}{\sum_{j\neq k} |h_{kj}|^2 p_j + \sigma_k^2}, \quad \text{.....(1)}$$

Where σ^2 denotes the noise power at receiver

$$\max_{p_1,\ldots,p_K} \sum_{k=1}^{K} \alpha_k \log\left(1 + \frac{|h_{kk}|^2 p_k}{\sum_{j\neq k} |h_{kj}|^2 p_j + \sigma_k^2}\right) \quad \text{....(2)}$$
$$\text{s.t.} \quad 0 \le p_k \le P_{\max}, \ \forall\, k = 1, 2, \ldots, K,$$

We are interested in power allocation for each transmitter so that where P_max denote the power budget of each transmitter; $\alpha_k > 0$ are the weights

4.Conclusion and Future Scope

In this work, we developed a wireless resource allocation mechanism based on DNNs. Our findings indicate that, with regard to power control issues like interference channel (IC). DNNs have minimal computational complexity and great sum-rate performance because they can closely mimic the behaviour of WMMSE. Our results are quite positive in many ways. The main takeaway is that DNNs can be very useful in solving real-time wireless resource allocation issues. Nevertheless, the work done so far only goes so far in terms of comprehending what DNNs (or similar learning algorithms) are capable of handling in these kinds of problems.

The study concludes that DNNs have significant promise for solving real-time wireless resource allocation issues. Due to DNNs' ability to accurately mimic the WMMSE's behaviour, sum-rate performance was high and computational complexity was low. To put it another way, DNNs have potential for wireless resource allocation, but further study is required to fully grasp their potential.

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