Optimal Resource Allocation and Data Communication in 5G and Beyond with a Cell-free IoTs Systems

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Abstract: In this paper introduced optimum data communication and resource allocation in a cell-free IoTs systems. The optimal resource allocation has been done to improve the quality of service (QoS). In this paper, depth limit search (DLS) algorithm is used for optimum resource allocation with the aid of machine learning (ML) technology. The simulation results show that the proposed method achieved the optimum throughput and spectrum efficiency compared to the conventional network.

Key Word: Cell-free IoTs, Machine Learning, Data Communication, Resource Allocation.

1. Introduction

It has long been difficult for the traditional cellular network to offer effective resources to cell edge users. The distributed cell-free network working in tandem with the radio frequency transmitter (RFT) is one of the methods for giving the cell edge user effective resources. In every way, the cell-free network performs better than the conventional [1], [2]. The user-centric clustering strategy has recently been established in the cell-free network to give the cell edge users with enough resources. In a user-centric clustering, the RFT centers users, allowing end users to get the needed resource from the cluster unit (RFT cluster), or the serving cluster built with the RFT to serve each user separately.

A vast network made up of numerous data-sensing devices connected to the Internet is known as the Internet of Things (IoT). The IoT intends to connect everything to the network to make identification and control easier. The IoT faces difficulties with regard to sustainability and dependability due to a growth in the number of devices, interconnectivity, and data volume. A cell-free IoT system based on a cell-free radio communication system is suggested to advance the IoT's growth. The cell idea for wireless transmission in the IoT system has been diminished under the design of cell-free IoT, and when compared to the cellular IoTs, the reliability and resilience of the IoT system can be increased.

The dependability and sustainability of the current IoT systems will face unprecedented challenges as the number of linked devices and the amount of data transmitted between IoT devices grows significantly [3-4]. The service life of sensors will be governed by the energy in the batteries because wireless sensors are powered by batteries [5]. The sensors will stop functioning when these batteries run out of power. A potential solution to this issue is wireless power transmission (WPT) [6-7]. Unfortunately, long-distance transmission and multitarget transmission are not effective with current WPT technology. At the same time, the IoT's rapid expansion of linked devices has significantly increased energy consumption, creating new environmental problems. Therefore, increasing energy efficiency (EE) is the best way to address the energy difficulties brought on by the development of the IoT [8-11].

In this article, we investigated the downlink MIMO-NOMA cell-free IoT. Contributions of these article are as follow:

- It offers a cell-free IoT that enables huge data transmission between system nodes and a connected network of connected things on a large scale.
- It evaluates the resource allocation (RA) issue and develops a power control-based EE optimization model for the cell-free IoTs.
- The RA problem is solved using ML techniques that is a recursive combination deep neural network (DNN) and DLS algorithm.
- It assesses the cell-free IoT system performance by taking into account a number of criteria and implements the EE managing the system.

2. System model

In fugure-1, the CPU, RFTs and IoT are connected to the users and IoT devices. It is the realistic way for fulfillment of the 6G and beyond technologies. For the wide extension of the wireless network, the cell-free IoT is the one of the perfect candidate technology. As shown in figure-1, all the CPUs C_n are connected to the cloud network; RFTs R_n are connected to the CPUs and IoT devices, and I_K IoT devices are connected to the RFTs. Time-division duplex (TDD) is the method used by RFTs to serve IoT devices. It is expected that CPUs have sufficient capacity for data transmission and reception. It is expected that data transfer is considered good QoS if IoT devices could transmit or receive information directly via CPUs. To achieve good QoS, data transfer through RFTs must be taken into account because of their restricted capacity. Data from IoT devices and/or users can be collected and sent to RFTs using an ad hoc network.

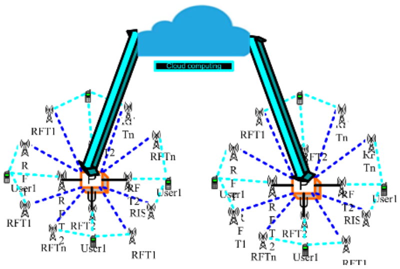

Figure-1: Cell-free IoT network

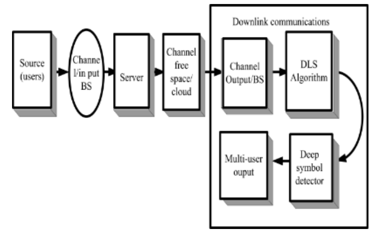

Figure-2: Source to Destination Data Flow in cell free IoT with DNN-DLSA

The channel gain g_{cn} is the coordination large scale fading and small-scale fading, it is represented as

$$g_{cn} = \sqrt{\beta} h_{ri}$$

Where β is the large-scale fading, h_{ri} is the Rayleigh fading channel coefficient between IoT device i and RFT R_n.In the uplink direction, the pilot sequence is sent to the RFT to determine the associated channel for IoT device. Hence, the equation for a pilot signal is represented as

$$y_{pr} = \sqrt{l^{CFU} \gamma^{CFU}} \sum_{i=1}^{n} g_{n\theta_n + W_n}$$

where, l^{CFU} is the length of the pilot symbol, γ^{CFU} is the signal to noise ratio of the pilot symbols received at the RFT,g_n is the channel gain between RFT and IoT device,. θ_n is the uplink pilot signal data, and W_n is the complex adaptive white Gaussian noise.

In the downlink data transmission, it does not require pilot symbol estimation, hence conjugate beam forming is used to estimate channels in both uplink and downlink directions. Then the received signals at the RFT is represented as

$$y_{r=\sqrt{\gamma^{CFU}} \sum_{i=1}^{n} g_i \sqrt{\alpha_i} q_i + W_{rn}}$$

where α_i is the power control coefficient of the n^{th} RFT, q_i is the transmitted symbol, W_{rn} is the complex Gaussian noise of the received RFT signal. It considers i^{th} IoT device, it requires P_i transmission power and measure the EE of the i^{th} user. The Total transmission power measured between IoT device and cell-free network via RFT. Basically, the EE is the ratio of data rate (DR) and total power consumption while transmitting the signals from source to destination. In another way the DR is calculated using the SE, that is product of SE and number cells per area. Then, the EE of the system is represented as

$$EE_i = \frac{DR}{P_T} = \frac{A \times SE}{P_T}$$

From the article [12], the SE is calculated using TDD protocol, which is represented as

$$SE_i = \frac{L}{l_c} E(\log_2(1 + SINR_i))$$

where, $SINR_i$ is the signal to noise ratio of the i^{th} user device received signal, $\frac{L}{l_c}$ is the transmission protocol of the TDD mode. The signal to noise ratio is

$$SINR_i = \frac{q_{i|h_i \gamma_i^{cpu}|^2}}{\sum_{i \neq k}^{K} q_{i|h_i \gamma_i^{cpu}|^2} + \sigma^2}$$

The throughput (Capacity) (bits/sec/hZ) of the system is measured as

$$\text{capacity} = \log_{10}(1 + SINR_i)$$

The throughput rate of the system is proportional to the SINR. Hence, above techniques used to measure the SE, throughput (TR) and EE.

3. Optimum Resource Allocation Algorithm

In this section we will discuss how to use ML to allocate the optimal power in cell free IoTs networks. A number of telecommunications-related issues can be easily solved with ML which is claim the authors of [13-15]. It can give trustworthy data, expedite operating procedures, and reduce mistake rates.

The data flow in the DNN-DLSA-enabled downlink connection from the BS to numerous users is shown in Fig. 2. A number of users can receive data thanks to the DNN network. Now, in order to ensure equity and provide adequate power to all consumers of poor signals, we must establish the long-term mean power (p_{avg}) value that will be utilized to regulate the power allocation system. This results in an average cumulative power rate that is constant over time.

$$\log_2\left(1+\frac{\beta^{\frac{1}{2}}\gamma_i\alpha_i}{\sum_{i\neq k}^{K}\beta^{\frac{1}{2}}\gamma_i\alpha_i+1}\right)+..+\log_2\left(1+\beta^{\frac{1}{2}}\gamma_1\alpha_1\right)-R_{avg}$$

The average power that is less than the sum of powers [16],

$$P_{i(max)} \geq \frac{noise\ power}{signal\ power}+\frac{1}{K}\sum_{i=1}^{K}\beta^{\frac{1}{2}}\gamma_i\alpha_i$$

$$P_{i(max)} > \frac{1}{K}\sum_{i=1}^{K}\beta^{\frac{1}{2}}\gamma_i\alpha_i$$

where β_l is the large-scale fading coefficient and $p_i(t)_{\max}$ is the ideal power level at the user's disposal. User 1 (UE1), who receives the least amount of power, consequently decodes its signal without interference. The DLSA is employed to carry out this strategy. The next sector provides an explanation of the DLSA's creation for MIMO-NOMA OPA in Downlink (DL) operations, and Figure-3 depicts the DLSA's workflow [17].

The DLS procedure for OPA under the DL approach is as follows:

Inputs of DNN,

$p_{avg,["X_1,X_2,X_3,......X_i"]}$, OPA to user with poor signal strength, bandwidth, the batch size, epochs, and learning-rate DNN output: supply of power $\{p_i, p_{i-1},......p_2, p_1\}$

i. Set b to be the batch size in order to provide input and output training.
ii. Create a DNN framework and begin a DLSA.
iii. Make a plan for allocating the best amount of power. Repeat t times more. Changing the value of range from 1 to i.
iv. Compare the output data [$\hat{x}_1, \hat{x}_2, ,......\hat{x}_i$] and the input data $\{x_i, x_{i-1}, x_{i-3}, ...x_1\}$ produced by the loss function action.
v. OPA to a user with a weak signal
vi. Bring it back / effective power allocation
vii. End

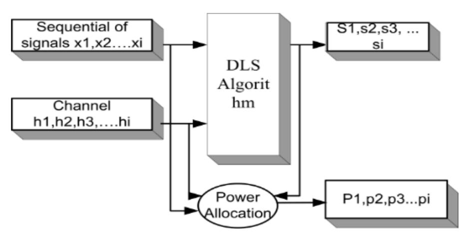

Figure-3: The DLSA for best resource allocation.

The DLSA offers the following benefits [18]:

The best DLSA is Adam's algorithm, which has the advantages outlined below:

i. Implementation in a clear-cut way
ii. Memory requirements are decreased.
iii. Effective computation
iv. Fixed diagonals have resized the gradient.
v. Most frequently, a moving object.
vi. Hyper parameters allow for straightforward iteration with minimal change.

4. Results and Discussion

In this section the simulation results are discussed in which various algorithms are implemented with MATLAB 2022b simulation software. We have assumed 1.5kmsq area and all parameters associate with its and their values included in table.1.

Table1. Parameters and its values.

Parameter	**Value**	**Parameter**	**Value**	**Parameter**	**Value**	**Parameter**	**Value**
Area	1.5ksq	Antennas	1-4	R_n	500	Path loss exponent α	4.02
power	0-12w	Channel gain	-144.25dB	I_K	200-300	Noise	9dB
Power control coefficient μ	0.6	C_n	2	B band width	20MhZ		

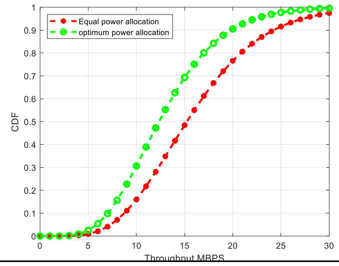

Figure-4: CDF vs. Throughput (Mbps) under different power allocation conditions.

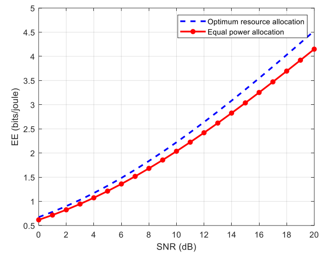

Figure-5: EE vs. SNR (dB), under different power allocation conditions.

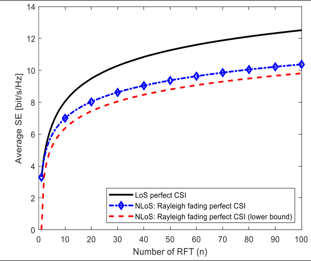

Figure-6: Average SE vs. number of RFT.

In Figure-4, commutative distributive function vs. throughput is observed in two different power allocation cases. In both cases, the cell edge user achieved the optimum throughput. The optimum resource allocation achieved a better result than the conventional resource allocation. Initially, the probability of achieving 10 MBPS is 30 percent in the case of optimum resource allocation and 18 percent in the case of equal power allocation. And finally, achieved 30MBPS in the case where optimum resource allocation is 100 percent and equal power allocation is 90 percent.

In Figure-5 EE vs. SNR shows that increasing the SNR increases the EE proportionally. Here, consider two cases those are optimum resource allocation and equal power allocation at RFT scenario. In the case of optimum resource allocation, the maximum EE is 4.5 (bits/sec), and equal power allocation is 4 bits/sec) at 20 dB SNR. Hence, the proposed result outperforms the conventional scheme.

In figure-6, the average SE ((bits/sec/Hz)) vs. number of RFTs is shown, consider both the LOS and NLOS Rayleigh fading channel. When the number of RFTs increases, the SE is also increasing exponentially. In this case, we consider different LOS and NLOS for the transmission of the data signal. In the case of LOS, the achieving effective SE is high, as observed with both perfect and impact channel state information. In the case of perfect CSI, the achieved SE is higher compare to other methods.

Conclusion

In the cell-free IoT, mobile users and IoTs are connected via RFT; therefore, coverage is wide and resource allocation becomes easier, and DNN with DLSA has provided optimal resource allocation to achieve optimal results. The cell-free IoT is directly connected with the cloud network which improve QoS. The simulation result that are shown in this paper has been performed by the DNN with DLSA to measure the SE, EE, and throughput. The cell-free IoT network outperforms the conventional cell-free network. The future direction of this research work is cell-free IoT with reconfigurable intelligent surfaces (RIS) to reduce power consumption and enhance both SE and EE.

Reference

[1]. Ngo, H.Q., Ashikhmin, A., Yang, H., Larsson, E.G. and Marzetta, T.L., 2017. Cell-free massive MIMO versus small cells. IEEE Transactions on Wireless Communications, 16(3), pp.1834-1850.

[2]. Nayebi, E., Ashikhmin, A., Marzetta, T.L., Yang, H. and Rao, B.D., 2017. Precoding and power optimization in cell-free massive MIMO systems. IEEE Transactions on Wireless Communications, 16(7), pp.4445-4459.

[3]. C.Kai,H.Li,L.Xu,Y.Li,and T.Jiang, "Energy-efficient device-to-device communication for green smart cities"IEEE Transaction on industrial forrmate.,Vol.14,no.4,pp.1542-1551,2018.

[4]. M.M.Mowla,I.Ahmad,D.Habibi,and Q.V.Phung, "A green communication model for 5G systems,"IEEE Transaction on Green communication networks.,Vol.1,no.3,pp.264-280,2017.

[5]. X.Zhang,X.Zhang,and L.Han, "An energy efficient Internet of things network using restart artificial bee colony and wireless power transfer,"IEEE Access,Vol.7,no.,pp.12686-12695,2019.

[6]. W.Na,J.Park,C.Lee,K.Park,J.Kim, and S.Cho, "Energy-efficient mobile charging for wireless power transfer in Internet of Things networks," IEEE Internet Things Journal,Vol.5,no.1,pp.79-92,2018.

[7]. Z.Wang, X.Yang,X.Wan,X.Yang,and Z.Fan, "Energy- efficiency Optimization for wireless power transfer enabled massive MIMO systems with hardware impairments," IEEE Access Vol.7,no.,pp.113131-113140,2019.

[8]. N.Kour, and S.K.Sood, "An energy-efficient architecture for the Internet of Things (IOT)," IEEE system of Journal Vol.11,no.2,pp.796-805,2017.

[9]. R.J.Carbajales, M.Zennaro,E.Pietrosemoli, and F.Freitag, "Energy efficient Internet of Things monitoring with low –capacity devices," in proceeding IEEE 2nd world Forum Internet Things (WF-TOT),Vol.,no.,pp.305-310,2015.

[10]. A.Burdett, "Ultra-low power wireless system : Energy-efficient radios for the Internet of Things," IEEE Solid –State Magazine .,Vol.7,no.2,pp.18-28,2015.

[11]. X.Zhang,Qi.H..X,and L.Han, "Energy-efficient resource allocation and data transmission of cell-free internet of things.,"IEEE Internet of Things Journals,Vol.8,no.20,pp.15107-15116,2020.

[12]. J.C,Z.H,R.Y,C.K and H.L, "Machine Leaning paradigms for Next –Generation Wireless Network," IEEE Wireless Communications,Vol.24,no.2,pp.98-10,2016.

[13]. Y.Lecun,Y.Bengio,G.Hinton, "Deep Laring ,"Nature,Vol.521,no.7553,pp.436-444,2015.

[14]. Xu.Yi.Han,Tian Yong.BO, K.Searyoh,Yu .Gang Yang,Y.Tiam, "Deep Reinforced Learning –based resource allocation strategy for Energy Harvesting –power Cognity Machine to-Machine Networks," Computer Communications,Vol.160,no.5,pp.706-717.

[15]. A.Zappone,M.Direnzo,and M.Debbah, "Wireless Network Design in the Era of Deep Learing :Model –Based ,AI-Based,or Both?, "IEEE Transaction on Communications,Vol.67,no.10,pp.7331-7376,2019.
[16]. B.Abdullah,S.Radosveta, "Massive connective with machine leaning for the internet of Things," Computer Networks,vol.184,no.7,pp.107646,2021.
[17]. R,Mancharla, and Y.Bulo, "A Comparative Analysis of the various Power Allocation Algorithm in NOMA-MIMO Network Using DNN and DLS Algorithm," EAI Endorsed Transaction on Mobile Communications and Applications, Vol.7.no2,pp.,2022.
[18]. M.Ravi,S.Ali Tasher, and B.Yaka, "Energy Efficiency and Resource Allocation Optimization with MIMONOMA and Backhaul Beam-Forming in User-Centric Ultra-Dense Networks," International Journal of Sensors, Wireless Communications and Control, 13(7),pp.,2022.

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