Machine Learning Based Throughput Enhancement in Fifth Generation Networks

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Abstract.. The 5G Enhanced Mobile Broadband (eMBB) category offers faster data rates, network capacity, and user experiences than prior generations. This research aims to boost the 5G uplink User Equipment (UE) user data transfer rate. We use Python to build frameworks and analyze data. A 250-m-radius center-excited Picocell Base Station (PBS) is investigated to support 15 clients. Cell-range Poisson distribution determines user position. All UEs send Channel State Information (CSI) to the PBS, which evaluates signal transmission channel conditions. The study uses Rayleigh, Rician, free space path, and long-distance route loss models. This inquiry produces a channel state dataset and then it is formulated dataset is dynamic. For service-specific requirements, UEs use K-means clustering. Clustering concatenates bandwidth, enhancing system efficiency and UE sum rate. Observations from simulation findings. UEs are grouped by channel gain, achievable data rate, and minimum service-required data rate. Users in cluster 3 achieve the highest cumulative rate of 9.09 Mbps after clustering with an average of 7.16 Mbps. Bandwidth concatenation increased system capacity, meeting each UEs service needs. After evaluating different clustering models performance criteria, K-means remains the best algorithm for the framework. The methodology was carefully designed to satisfy study goals. This research will investigate beamforming and dynamic clustering to improve user fairness and performance.

Key words: *5G; Channel State information; Bandwidth; Machine Learning; Clustering;*

1. INTRODUCTION

Fifth-generation (5G) wireless technology is the latest mobile communication standard. 5G builds on its predecessors to improve capacity, decrease latency, speed up data transfer, and support a large number of networked devices. [1]. This cutting-edge technology can alter transportation, healthcare, telecommunications, and entertainment, as well as improve user experiences through faster downloads and uninterrupted connectivity [2].

5G technologies limited global coverage, which benefits metropolitan areas, is one of its main drawbacks [3]. Remote places may not get 5G for years. Although 5G technologies limit transfer speeds to 100 Mbps, they offer rapid download rates, marking a significant improvement over 4G. Mobile phone battery technology must also improve for 5G to work. 5G supports many use cases, including Massive Machin Type Communication (mMTC), Enhanced Mobile Broadband (eMBB), and Ultra Reliable Low Latency Communication (URLLC), are the most popular services.

Sum rates are the maximum data rates available to all users in an area at the same time. This essential parameter affects network capacity and user experience. 5G optimises spectrum efficiency, interference control, and resource allocation to maximise the total rate. This enhancement speeds up data rates, lowers latency, and improves bandwidth-intensive applications like UHD video streaming, Virtual Reality (VR), Augmented

Reality (AR), and Internet of Things (IoT). To efficiently serve many customers and supply varied services with reliability, we need high sum rates [4].

Sum rate is critical in 5G as a performance indicator that accurately captures communication systems total data throughput, especially in multi-user scenarios. Maximising the overall rate enhances network capacity and throughput [5]. 5G networks can handle more users and provide higher data rates by optimising resource allocation to optimise the total rate, increasing Quality of Service (QoS) metrics like latency and reliability. Sum rate optimisation ensures network adaptation in dynamic communication contexts [6]. However, complex optimisation methods and advanced interference control solutions make it challenging to achieve the greatest data transfer speeds in 5G networks. Sum rate optimization's susceptibility to channel fluctuations and performance measure concessions may make stability and scalability in large networks difficult. Despite these challenges, sum rate optimisation research and development emphasise the need to improve 5G communication systems [7].

The 5G service category of eMBB offers faster data rates, network capacity, and user experiences than prior generations. It aims to achieve speeds of multiple gigabits per second. This speeds up the transfer of huge files, HD videos, and data-intensive applications. It decreases the duration of data transfer between the user device and the network server. Online gaming,

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VR, AR, and interactive multimedia services have data rate requirements [8].

5G networks can accommodate several users accessing and transmitting data without sacrificing performance. 5G uses sophisticated modulation, massive MIMO, beamforming, and spectrum sharing to maximise spectral efficiency [9]. This optimises frequency spectrum use, enhancing network capacity and data throughput for improved eMBB services.

High-speed data transmission is in demand, so modern communication systems must optimize sum rates, which indicate data throughput. Heuristics and inflexible resource allocation algorithms may not fully leverage dynamic and complicated communication settings [10]. Machine Learning (ML) can optimise communication system components by utilising data-driven insights to enhance sum rates [11]. Channel prediction is machine learning's specialty. ML models can predict channel conditions based on historical data. These models anticipate path loss, fading, and interference to optimise transmission parameters for channel stability and sum rates [12]. Based on real-time feedback and optimisation goals, the algorithms can dynamically distribute bandwidth, power, and time periods. Intelligent resource allocation lets ML-driven systems get the highest sum rates while also being fair and efficient in network environments that are very dynamic and different [13]. Advanced machine learning can optimise channel prediction, resource allocation, interference control, and modulation methods to boost communication system total rates [14].

The main objective of this research is to investigate the throughput of users using ML models such as K-Means, Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and Gaussian Mixture Model (GMM), with the aid of clustering. This is achieved by calculating the silhouette score and the Davies Bouldin Index (DBI).

The remaining sections of the paper are summarized as follows: Section 2 delves into current research on enhancing throughput in 5G networks, while Section 3 explores the current status of the proposed effort and technique. Section 4 discusses the simulation circumstances, then proceeds to an investigation of clustering using ML models. Finally, Section 5 summarizes the outcomes of the scenarios studied before and after clustering, as well as the future scope.

2. LITERATURE SURVEY

The authors in [15] introduced an approach that utilises unsupervised machine learning and conditional independence tests (CITs) to detect network performance trends based on data. We assessed the technique by utilising crowdsourcing data from 5G UEs and a dataset from a Long-Term Evolution (LTE) network, using the K-Means clustering algorithm. The findings indicated that the uplink throughput, as assessed, had the greatest impact on the observed performance patterns. The LTE dataset also demonstrated a link between the amount of signalling resources assigned in the Physical Uplink Control Channel (PUCCH) and the uplink data transfer rate of the user equipment. Deep learning algorithms specifically designed for

analysing time-series data will expand the technique in the future.

In [16], the authors presented a scheduling technique for full-duplex wireless networks that uses reinforcement learning for clustering users to optimise the allocation of network radio resources. The algorithm does not require user-to-user channel estimation. The study introduced a reinforcement learning method for scheduling in OFDMA wireless networks, with the goal of simplifying the scheduling process and improving spectral efficiency. The algorithm exhibited exceptional performance in scenarios involving the clustering of user equipment. The approach fails to address inter-cell interferences and instead concentrates solely on single-cell situations. Future research will focus on situations involving multiple cells and scheduling techniques.

The authors of [17] came up with a better K-means clustering method that uses Non-Orthogonal Multiple Access (NOMA) for 5G cellular wireless networks. The algorithm's objective is to achieve balance between the overall network throughput and fairness among devices, compared to the Random-Access Channel (RACH) in LTE. Designate the devices with higher channel gain as cluster heads to enhance the overall network throughput. The research work has outperformed typical K-means by achieving a higher sum throughput in the network. We apply the algorithm iteratively to the remaining network to obtain the optimal solution for the cluster formation problem.

In [18], the authors have studied user clustering and power allocation schemes based on reinforcement learning for the NOMA system. The authors employ the Q-learning technique to optimise power allocation and maximise the aggregate data rate. The authors deploy the K-means algorithm to cluster users based on channel gain, thereby aiding in data rate maximization Extensive simulations confirm that the developed Q-learning technique with user clustering performs better than other scenarios, achieving the highest sum data rate. Additionally, it is capable of overcoming several NOMA constraints, such as transmission power budget limitations and minimum user data rate requirements.

In [19], the authors have worked on enhancing user capacity and optimizing power allocation, taking into account the subchannel assignment constraints in wireless networks. The authors have calculated channel data using the Shannon capacity formula and employed multiple linear regression models. We have generated test data to predict the sub-channels' capacity and use it to solve optimisation models. The model used linear regression equations as constraints, while treating power and capacity as variables. The study also investigated the enhancement of wireless networks by allocating distinct network segments to users in order to predict network performance.

In [20], the authors have examined the application of ML algorithms in green cellular networks for optimising Quality of Services (QoS), signal traffic load, and energy efficiency. The work additionally addressed the concept of Coordinated Transceiver Multipoint (CoMP) in TE-Advanced networks, which enhances network coverage and improves data rate. The study explored the power efficiency of green cellular

communication while considering quality of service (QoS) constraints. It also highlights the power levels required for transmitting bits and analyses the relationship between power consumption and latency caused by bandwidth limitations. The paper also addressed the trade-off between energy efficiency and spectral efficiency for cellular networks.

The authors of [21] suggested a new way to group users in the downlink of the 5G NOMA system that uses artificial neural networks (ANN) to get the most out of the system while keeping complexity low. The authors train the ANN model using a historical dataset, which includes transmitting powers, channel gains, and user cluster information of NOMA users. After that, the model is validated to find the best hyper-parameters. This keeps the model from overfitting and lets us accurately predict how clusters will grow. The simulation results of an ANN-based user clustering framework outperform traditional orthogonal multiple access (OMA) techniques, achieving optimal throughput performance in comparison to the Brute force method while maintaining an acceptable level of clustering complexity.

In [22], the authors presented a rapid-learning system called extreme learning machine-based user clustering (ELM-UC). The authors designed this scheme to operate in NOMA environments, quickly estimating the optimal formation of user clusters based on their channel gains and powers. The ELM design is well-suited for UC optimisation, as it operates as a predictor using significant input data. ELM-UC methodology delivers performance that is almost ideal when compared to the brute-force search (B-FS) method. Furthermore, it surpasses existing clustering strategies such as ANN-UC and dynamic user clustering (DUC). The offered ELM-UC scheme aims to address the issue of extended learning times in neural network-based UC schemes. It achieves this by solving the output weights in a single step, eliminating the necessity for a time-consuming backpropagation learning process.

The above literature discusses different system models with constraints to improve 5G sum rate through user clustering, power optimisation, beam forming, and other ML algorithms. However, the research work has limitations, such as considering a single fading environment and not specifying the exact system scenario for deployment.

To overcome these restrictions, the proposed system scenario incorporates a real-time visible pico-cell base station in a hexagonal cell. Examined multiple channel conditions and path loss models during dataset construction to match real signal propagation channel circumstances. We studied performance indicators for several models to find the optimal clustering algorithm. This research not only attempts to improve the 5G sum rate through user clustering, but also to meet the service needs of all eMBB users in the cell, which is novel.

3. PROPOSED METHODOLOGY

This section discusses the deployment of a picocell system and the creation of a tailored dataset. It details the steps for computing channel parameters for users and analysing channel capacity to meet service-specific requirements, aiming to enhance the sum rate via user clustering algorithms. The

chapter covers model construction and assesses the effectiveness of clustering in addressing diverse service needs.
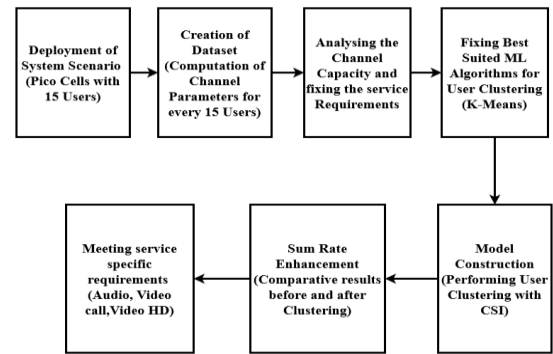

Fig.1. Block Diagram of the Proposed work

It aims to demonstrate the proposed methodology efficacy in optimizing system performance and ensuring seamless service delivery through careful examination and comparative analysis. Figure 1 presents the block diagram of the proposed ML-based throughput enhancement system.

3.1. System Model

Deploying the Picocell system with 15 users creates the operational environment for future data collection, analysis, and optimization. It places the work in a real-world context, allowing for practical insights and outcomes.

The dataset construction is crucial as it provides the raw data needed for analysis and optimization. By computing channel parameters for each user, it captures diverse real-world channel conditions. This extensive dataset forms the basis for analysis, enabling informed decision-making and optimisation strategies. The CSI equations analyse free space, log-distance path loss, Rayleigh, and Rician fading channels [23]. The model calculates SINR, communication quality metric, after channel gain. Using SINR values, the model calculates each user channel capacity, which is the maximum data rate under certain conditions.

The pathloss can be shown as

$$FSPL = 20 * \log_{10}\left(\frac{4\pi d}{\lambda}\right) \tag{1}$$

$$LDPL = 20 * log_{10}\left(\frac{4\pi}{\lambda}\left(\left(\frac{d}{d_0}\right)^n\right)\right) \tag{2}$$

where d_0 is the reference distance, FSPL is the Free Space Path Loss [24], LDPL is the Log Distance Path Loss [24], λ is the wavelength and then n is the path loss exponent.

The Rayleigh Channel can be calculated as shown in the equation 3

$$f(x) = \frac{x}{\sigma^2}\mathrm{e}\left(\frac{-x^2}{2\sigma^2}\right) \tag{3}$$

The Rician Channel can be calculated as shown in the equation

$$f(x:K) = \frac{2(k+1)}{k}\mathrm{e}^{-k-1}I_0\sqrt{k(k+1)x} \tag{4}$$

where x being a signal power, σ is the Standard deviation, k is the cluster size and K is the Normal Distribution. The channel gain can be calculated and SINR

3

$$H = 10^{-\alpha/20} * \beta \tag{5}$$

$$\Gamma = 10 log_{10} \left\{ \frac{P_{signal}}{P_{interfernce} + P_{noise}} \right\} \tag{6}$$

The Capacity can be calculated as

$$C = B log_2 (1 + SINR) \tag{7}$$

where α is the Pathloss Component, β be the Signal Power, C is the Capacity of the user, SINR be the Signal to Interference plus Noise Ratio and B is the Bandwidth.

The system model closely interconnects the derived parameters, namely channel gain, SINR, capacity, and sum rate. Channel gain, determined by path loss and fading factors, directly influences SINR. With respect to interference and noise, the strength of the received signal increases, resulting in a higher SINR value. SINR, in turn, plays a pivotal role in calculating channel capacity, following Shannon's capacity formula, where higher SINR values lead to increased capacity. The individual capacities of user channels, influenced by their respective SINR values, collectively contribute to the overall sum rate of the system. So, changes in channel gain can affect SINR and capacity calculations, which in turn affect the sum rate by changing the total data rate of all users in the system. The Sum Rate can be calculated as

$$Rsum = \sum_{i=1}^{N} c^i. \tag{8}$$

where, $Rsum$ is Sum Rate and c^i be the Capacity of the users varies from 1 to N. Furthermore, the model extends its analysis to encompass the collective performance of all users within the picocell through sum rate calculation. This computation aggregates individual capacities to provide insights into the system's overall capacity. This systematic approach ensures a thorough understanding of the system behaviour under diverse channel scenarios, laying the groundwork for subsequent analysis and sum rate enhancement.

3.2. Channel Capacity Analysis.

Analysing channel capacity and fixing service requirements is critical for ensuring that the system meets users demands and expectations. This research optimizes the system's ability to deliver high-quality communication services by assessing channel capacity and aligning it with service-specific requirements. This step sets clearly defined performance benchmarks and objectives for the optimization process. According to 3GPP standards [25], Table 1 tabulates the minimum data rate required for the services considered under the eMBB application.

TABLE 1. eMBB Service requirements

Services	Specifications	
	Data rate	64 Kbps
	Channel	Stereo
Audio	Sample Rate	44 KHz
	Format	MP3
	Data rate	1.5 Mbps

Video Call	Resolution	720p
	Video Compression Standard	H265
	Data rate	5 Mbps
Video HD	Resolution	1080p
	Video Compression Standard	H265

Each UE is assigned a fixed service that is demanded by them and their minimum required data rate ranging from 0.064 Mbps to 5 Mbps.

Resource allocation and system optimization depend on choosing the best ML technique for user clustering. We chose k-means clustering over density-based scanning (DB-Scan) and the Gaussian mixture model (GMM) because it groups users quickly based on channel characteristics, which makes the best use of resources and improves system performance. This decision sets the stage for model building. This research implements user clustering using machine learning algorithms, particularly k-means clustering, with the aim of improving the sum rate. The suggested study used K-means, DB-scan, and GMM ML techniques to cluster users. The study uses machine learning performance evaluation metrics such as silhouette scores and Davies Bouldin indices to select between these models. This proves that K-means is the best clustering algorithm for the database.

3.3. Model Construction and Sum Rate Analysis.

Model building is essential for turning raw data into actionable insights. User clustering using Channel State Information (CSI) data reveals channel condition trends. This allows targeted tuning. This phase lays the groundwork for optimizing system performance and sum rate.
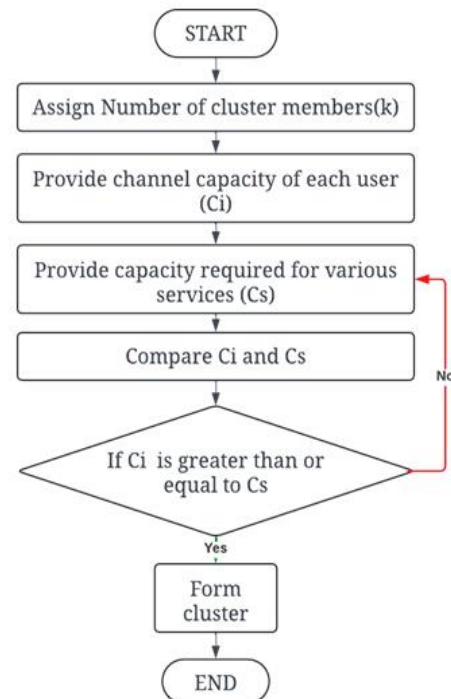

Fig.2. Working of K-means based user Clustering

Figure 2 depicts the flowchart for the workings of the K-means clustering algorithm in the proposed system scenario.

Where k denotes the number of clusters (k = 3), Ci is the computed capacity of each user, and Cs is the required capacity for specific services. We position the users into a cluster by maintaining the computed cluster capacity above the required data rate.

Evaluating the achieved sum rate before and after clustering provides a quantitative measure of the effectiveness of the optimization strategy and by comparing system performance metrics, the project assesses the impact of user clustering on overall system throughput. This comparative analysis adheres to excellent decision-making and optimization efforts, guiding future enhancements and improvements.

Meeting service-specific requirements is paramount for ensuring user satisfaction and system usability. This research work aims to meet the service demands of all eMBB users in the hexagonal cell. By prioritizing the allocation of system capacity toward meeting these requirements, it ensures an optimal user experience across diverse communication modalities. This focus on service quality and user satisfaction underscores the commitment to delivering practical and impactful outcomes.

4. RESULTS AND DISCUSSION

These simulation settings are customized to match real-world conditions and it can be performed using Python. Our analysis also includes key performance metrics derived from comprehensive simulations. This detailed analysis compares system performance both before and after clustering. Clustering methods show advantages by enhancing system performance. We also provide a comprehensive review of user clustering machine learning algorithms.

4.1. Simulation Parameters.

Deploying the Picocell system with 15 users creates the operational environment for future data collection, analysis, and optimization. It places the work in a real-world context, allowing for practical insights and outcomes. Table 2 tabulates the considerations for this research.

TABLE 2. Simulation Parameters

S. No	Parameters	Values
1	Number of UEs	15
2	Cell Type	Pico Cell (100-250 m)
3	Path Loss	Free Space and Log Distance
4	Fading Channels	Rayleigh and Rician
5	Number of Pico BS	1
6	Carrier Frequency	6 GHz
7	Bandwidth	10 MHz
8	Transmit Power	30 dBm

4.2. Performance metrics.

This study calculates the capacity and sum rate for each UE in the system under consideration. For the system scenario, we obtain the following simulation parameters for the free-space

Rayleigh fading channel. Table 3 and 4 computes the channel gain, SINR and Sum rate.

The channel gain influences the signal strength, coverage, and throughput of the user equipment (UEs), ensuring the QoS in the simulated environment. SINR is then used by determining the performance and capacity of the 5G networks to calculate the sum rate of the users, and Table 3 shows the results of the channel gain and SINR value; it achieves a moderated SINR value of 5dB to 12dB, making it suitable for mobile broadband users.

The sum rate determines the network overall capacity; it's performed by maintaining QoS to improve user experience and make better use of available resources, and as shown in Table 4, it achieves roughly 2 Gbps for mobile users.

TABLE 3. Computation of Channel gain and SINR

UE ID	Distance (m)	Channel Gain	SINR (Watt)
1	131	2.29826E-05	0.007524608
2	137	7.10471E-05	0.003667752
3	147	1.97082E-05	0.017823362
4	155	3.18995E-05	0.007800755
5	137	4.55325E-05	0.000531125
6	162	2.26961E-05	0.011070093
7	138	4.79879E-05	0.01448357
8	147	4.93726E-05	0.02258521
9	158	3.08838E-05	0.00573407
10	145	5.22657E-05	0.004169871
11	156	2.70481E-05	0.013023036
12	134	5.2124E-05	0.011908173
13	141	8.57054E-05	0.016861267
14	159	3.06909E-05	0.007925278
15	145	3.13109E-05	0.004908504

TABLE 4. Computation of User Sum rate

UE ID	Distance (m)	SINR (Watt)	Sum Rate (Gbps)
1	131	0.007524608	1.08
2	137	0.003667752	0.52
3	147	0.017823362	2.54
4	155	0.007800755	1.12
5	137	0.000531125	0.07
6	162	0.011070093	1.58
7	138	0.01448357	2.07
8	147	0.02258521	3.22
9	158	0.00573407	0.82
10	145	0.004169871	0.06
11	156	0.013023036	1.36
12	134	0.011908173	1.70
13	141	0.016861267	2.41
14	159	0.007925278	1.13
15	145	0.004908504	0.07

4.3. Performance analysis.

This section includes an analysis of performance metrics, specifically the sum rate and ML model evaluation metrics. This includes comparing the sum rate before and after

clustering, as well as comparing three different ML models to select the most suitable model for user clustering.

Table 5 lists each users system capacity, along with the minimum capacity needed to meet the service-specific throughput requirements for that user. Among fifteen users, nine users met their minimum service requirements, whereas the remaining UEs were not able to satisfy the minimum service requirement. Only sixty percent of the users were able to meet the requirements.

TABLE 5. Capacity of the System before clustering

UE ID	Distance (m)	Throughput Before Clustering	Service Demanded	Minimum Service Required	Service Met
1	131	1.08	Audio	0.064	Yes
2	137	0.52	Audio	0.064	Yes
3	147	2.54	Video Call	1.5	Yes
4	155	1.12	Video_Hd	5	No
5	137	0.07	Audio	0.064	Yes
6	162	1.58	Video Call	1.5	Yes
7	138	2.07	Video_Hd	5	No
8	147	3.22	Video Call	1.5	Yes
9	158	0.82	Audio	0.064	Yes
10	145	0.06	Video Call	1.5	No
11	156	1.36	Video Call	1.5	No
12	134	1.70	Video Call	1.5	Yes
13	141	2.41	Audio	0.064	Yes
14	159	1.13	Video_Hd	5	No
15	145	0.07	Video Call	1.5	No

Figure 3 displays the UEs that belong to each cluster after clustering, along with their coordinates in the picocell. Different shapes denote UEs belonging to three different clusters.
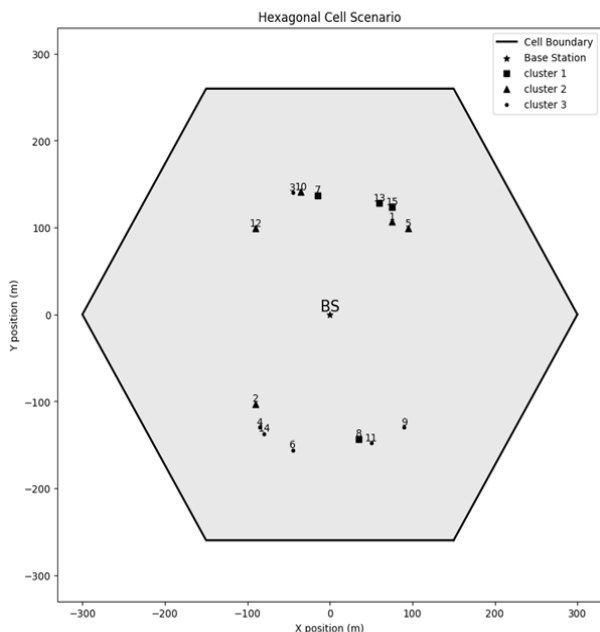

Fig.3. Picocell scenario after Clustering

Figure 4 represents a unique cluster of users, classified based bandwidth and SINR, calculates the total rate. Therefore, clusters with higher sum-rate bars indicate superior network performance in meeting the service requirements of UEs inside such clusters. Furthermore, we compute the average throughput for all clusters to be 7.16 Mbps.
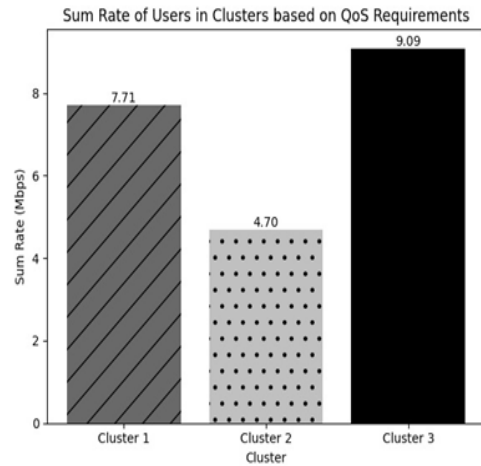

Fig.4. Capacity after cluster formation

Picocells are used after clustering to optimize network performance. They achieve this by improving the user experience, enhancing user capacity to prevent interference, and ultimately enhancing the quality of service for consumers through throughput enhancement.

Figure 5 shows which cluster the UE belongs to and its distance from the BS.

The distances within the cluster, which comprises three users, are much closer than the other clusters. Cluster 1 has smaller distances; this means the cluster members are likely to be close or far apart depending on the distances given. Cluster 2 is located on the opposite side, and the distance between it and the other two clusters is significantly smaller than that of Cluster 1 and significantly larger than that of Cluster Such an approach could potentially detect trends in user distances, as well as investigate aspects such as user behavior, regional distribution, and future network construction.
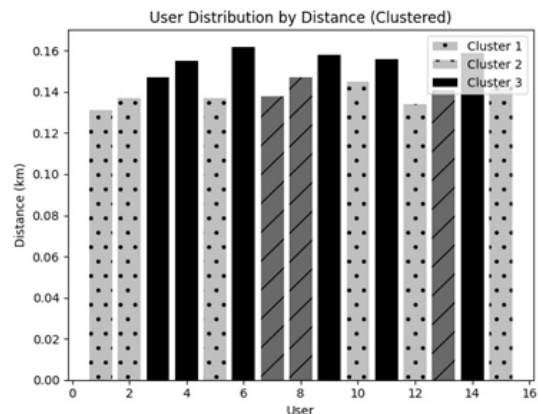

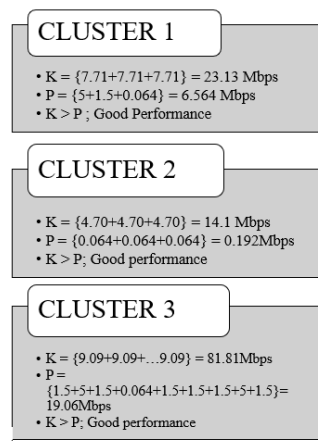Fig.5. Distance of user inside picocell

Fig.6. Maximum achievable capacity for each cluster

Figure 6 depicts the maximum achievable capacity for each cluster (k) and the minimum required capacity (P) for that cluster to satisfy every UE service-specific requirement.

The combined SINR values for each cluster are given, providing information on the signal quality that users in these clusters experience. Aggregate SINR for each cluster: [0.053, 0.032, 0.063]

When approaching the first base station, the throughput after clustering proves just 4.70 Mbps—about a factor of two lower than what it is without base stations routing information into place. As the distance from the base station increases, after clustering, throughput seems relatively stable an effect that suggests improving longer distances. Clustering maintains high throughput within a specific range or across all ranges. Even at the further distance of 156 meters, throughput is still 9.09 Mbps, which is quite good for video calls and HD video streaming.

After clustering, the throughput reaches its peak in the process, maintaining or surpassing the minimum service for all users, regardless of their distance from the base station.

TABLE 6. Capacity of the System after clustering

UE ID	Distance (m)	Throughput After Clustering	Service Demanded	Minimum Service Required	Service Met
1	131	4.70	Audio	0.064	Yes
2	137	4.70	Audio	0.064	Yes
3	147	9.09	Video Call	1.5	Yes
4	155	9.09	Video_Hd	5	Yes
5	137	4.70	Audio	0.064	Yes
6	162	9.09	Video Call	1.5	Yes
7	138	7.71	Video_Hd	5	Yes
8	147	7.71	Video Call	1.5	Yes
9	158	9.09	Audio	0.064	Yes
10	145	4.70	Video Call	1.5	Yes
11	156	9.09	Video Call	1.5	Yes
12	134	4.70	Video Call	1.5	Yes
13	141	7.71	Audio	0.064	Yes
14	159	9.09	Video_Hd	5	Yes
15	145	4.70	Video Call	1.5	Yes

Hence, picocell clustering has likely enhanced and relayed the capabilities of the network and suppressed interference, thus allowing users, even if they are situated a maximum of 156 meters away, to receive a very high throughput that satisfies their service requirements.

Table 6 illustrates how the capacity after clustering enables each user to meet their service requirements, as the minimum required throughput is less than the obtained capacity after clustering. This ensures that clustering increases the overall system capacity, thereby enhancing the throughput of the entire system and meeting service-specific needs for every single user.

4.4. ML model comparison

We test different ML models for user clustering. We use the silhouette score and Davies-Bouldin index. We test all clustering models, including k-means, DBSCAN, and Gaussian Mixture Models (GMM), to divide UEs into clusters.

Higher silhouette ratings indicate more distinct clusters and levels of cohesiveness and separation. However, the Davies-Bouldin index evaluates cluster separation by comparing cluster centroids and diameters; lower values indicate better clustering. A careful analysis and comparison of these measures across multiple clustering models reveals each technique's subtle pros and cons.

Table 7 shows that the k-means algorithm outperforms the other two models by obtaining better evaluation scores for both metrics.

TABLE 7. Clustering performance of ML models

S. No	ML Model	Silhouette Score	Davies Bouldin Index
1	K-means	0.343	0.8144
2	DBSCAN	0.196	2.006
3	GMM	0.285	1.0598

5. CONCLUSIONS

To conclude the system deployment scenario, we examined four different channel scenarios, each involving combinations of fading channels and path loss models. We developed a thorough dataset with 15 users, each distinguished by specific channel parameters and service requirements tailored to their unique needs. The demonstration of the K-means machine learning method for user clustering showed encouraging results in optimizing system efficiency, improving the overall sum rate, and fulfilling user service requirements.

In the future, researchers may focus on using advanced machine learning techniques, such as Extreme Learning Machines (ELM), K-means, convolutional neural networks (CNNs), and deep neural networks (DNNs), to compare how well different methods work. Additionally, explore beamforming systems that focus on improving signal delivery to individual users. Real-time feedback on Quality of Service (QoS) can guide the implementation of dynamic user clustering processes. This will lead to ongoing enhancements in network performance and user satisfaction.

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