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Performance Analysis and Optimal Cooperative Cluster Size for Randomly Distributed Small Cells Under CAN Protocol

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ABSTRACT
The ease of imposing multicell coordination mechanisms to enhancing system spectrum efficiency (SE) and performance estimate is one of the key advantages of cloud/centralized control area networks (CAN). Enormous number of cooperative cells should theoretically result in a higher SE, but they may also cause considerable delays due to extra channel state information (CSI) feedback and joint processing computing needs at the cloud data centre, resulting in performance deficit. I partition the network into numerous clusters of cooperating tiny cells and create a throughput optimization problem to study the impact of delays on throughput gains. As a function of cluster size, I figure various delay factors and the network's sum-rate, treating cluster size as the fundamental optimization variable. For both linear and planar network installations, I treat both base station and user geometric locations as random variables in my study. On the basis of the homogeneous Poisson point processing (PPP) model, the output SINR (signal-to-interference- plus-noise ratio) and ergodic sum-rate are calculated. The sum-rate optimization problem is formulated and solved in terms of cluster size. The suggested analytical framework may be used to precisely evaluate the performance of practical cloud-based small cell networks via clustered cooperation, according to simulated study.
Keywords— Control Area Network, Spectrum Efficiency, Channel State Information

1. Introduction

Control Area Network (CAN) protocol has gotten a lot of attention from academics and industry in recent years as a possible candidate technology for next-generation wireless communications. Apart from the cost-cutting benefits of CRAN, another advantage is the ease with which multi-cell coordination techniques such as Coordinated MultiPoint Transmission and Reception (CoMP) can be implemented, resulting in improved system performance through effective interference management[9].
One of the most common functional splits in a CAN is to use a central processor with strong computing capabilities to handle high-complexity jobs in the cloud, and a group of denselydeployed, low-power, low-complexity Radio Remote Heads (RRHs). This solution can take advantage of the low-cost benefits of building a dense small cell network while also utilising centralised processing to achieve efficient interference avoidance and cancellation techniques across several small cells in order to increase network spectral efficiency (SE).

2. Experimental Methods or Methodology

The Non Orthogonal Multiple Access (NOMA) technique is one of the more recently presented

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concepts aimed at meeting the expectations of mobile consumers in 5G networks. With single-antenna transmitters and receivers in each cell, base station coordination with dirty paper coding was first presented in. There are numerous sub-optimal joint transmission techniques with per- base power limitations, as well as a dirty paper coding solution with perfect data and power cooperation among base stations with a pooled power constraint.

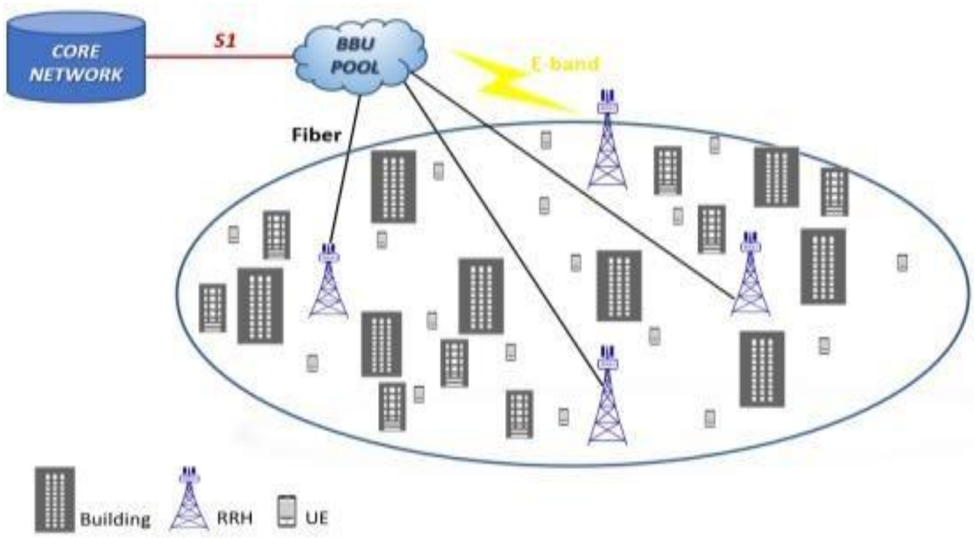

Fig1.Interface between the core network and RRH

The goal of my research is to improve the throughput of edge users in a 5G small cell CAN network where NOMA and MU-MIMO are coupled and user mobility is a concern, without degrading the performance of non-edge UEs significantly[3]. Implementing JT-CoMP, in which transmission point clustering is based on a coalition building game that takes into account the costs of cooperation and can adjust to the dynamic nature of the given scenario, is the chosen method. Furthermore, the obtained results are compared to those of a no-CoMP case, a case where transmission point clustering is done in a static manner, and a case where a dynamic greedy clustering algorithm is used to confirm the effectiveness of the proposed scheme in reliably and constantly mitigating intercell interference and enhancing mobile user performance.

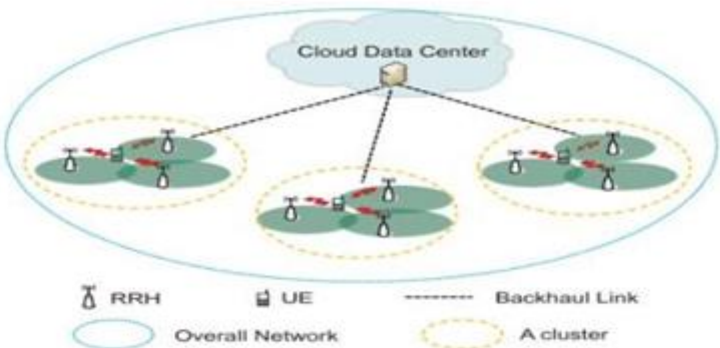

Fig2.Intercell Interference

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As a result, each RRH in a cooperative cluster can only acquire a nearby CSI, whereas worldwide CSI is accumulated at the cloud via backhaul links by RRH feedback. Calculations for the precoding matrix will be done in the cloud. However, there are two primary options for precoding implementation: a) implementing at the cloud and then forwarding the precoded I/Q signals to individual RRHs for transmission; and b) cloud- assisted implementation at each individual RRH, in which the modulated I/Q signal (before precoding) and relevant precoding coefficients will be sent from the cloud to each RRH and the rest of the physical layer processing will take place in the RRH.

3. Results and Discussion

I study the proposed clustering optimization trouble with ZF and MRT precoding strategies for linear and planar dense small cell deployments using Monte-Carlo simulations[14]. 1000 tiny cells and 1000 active UEs are dispersed uniformly in a) a circular network area (planar deployment) with a radius of 500 metres and b) a linear network segment (linear deployment) with a length of 1000 metres. I'm going to presume that each RRH has two antennas. To approach a circle-bounded network in planar deployment, I assume clusters built by 1 to 7 tiers of cells, i.e., cluster size will take values from the range set if tier-1 consists of 7 cells, tier-2 of 19 cells, and so on. The signal-to-noise ratio (SNR) of the input signal is adjusted to 30dB. As shown in equation, the path-loss exponent is retained at 2.2, and Rayleigh fast fading is used to describe channels between RRHs and UEs. For all links, the temporal correlation of the channel is represented using an equation with Doppler spread fD = 10 Hz. R0 = 5 metres in both linear and planar deployments. We only analyse the performance of the UEs in the central cluster for the sake of generality, and we assume that interference from outside the network to these UEs is insignificant.

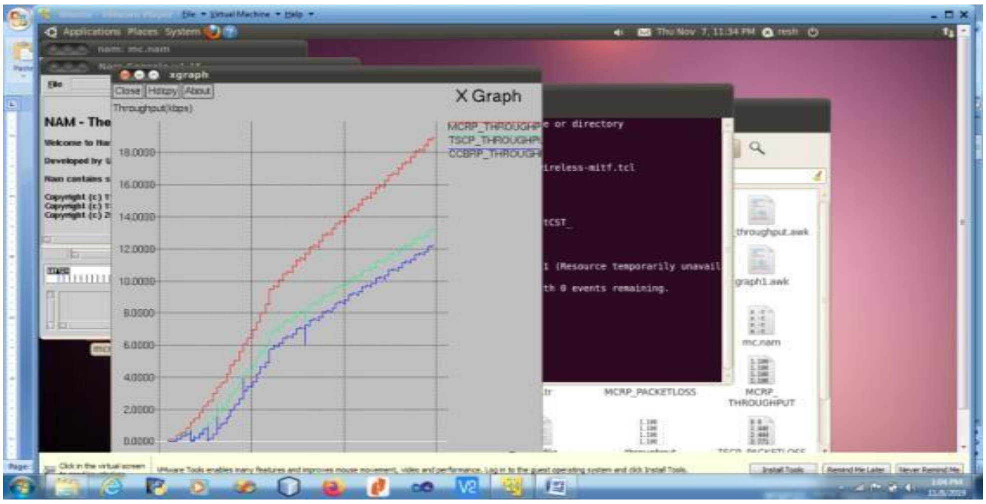

Fig3. Throughput vs energy graph

Output SINR in the absence of latency:

To test the effectiveness of our theoretical analysis (i.e., the suggested system, channel, and clustering model in Sections III and IV), we first calculate P x, P I, and output SINR without delay, i.e., t = 0 and 2 = 1. For varying numbers of clusters inside the network, P x and P I are calculated using equations for planar deployment and compared to simulation findings in Fig.4. For both planar and linear deployments, the analytical results for both the required signal and interference power match the simulation results completely. The required signal power decreases with cluster size (i.e. the number of clusters in the network), as expected, because there are fewer collaborating tiny cells

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contributing to the desired power. The interference power, on the other hand, grows as the number of clusters grows since the total number of interfering RRH outside the cluster grows. In addition, the output SINR is evaluated using MRT and ZF precoding equations, and the results are compared to simulation findings in Fig. 7.1. I see good consistency between analytical and simulation results in all four graphs (Linear-MRT, Linear-ZF, Planar-MRT, and Planar-ZF)[14]. In all circumstances, the output SINR drops as thenumber of clusters increases, because a smaller cluster obtains less desired signal power while experiencing more interference from outside the cluster. Due to the assumptions applied in the clustering approach, there are slight discrepancies between theoretical and simulated results.

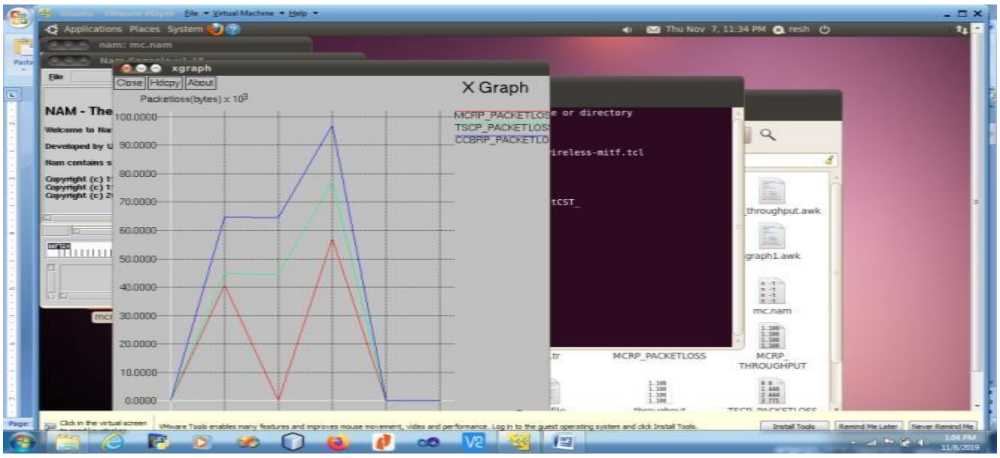

Fig4.Packet loss time based graph

I find that the analytical results closely match the simulation results, particularly for output SINR. More importantly, for any given configuration, the peak points denoting the optimal cluster size are strictly overlapping; thus, the optimal cluster size evaluation is unaffected by the approximation in equation where Jensen's inequality and the upper bound of the sum- rate are taken into account (obviously, the theoretic sum-rate for each qc is generally higher than the simulated results). I also notice that when the computational capability factor grows greater, the optimal cluster size drops (and the optimal number of clusters increases). This is because when qc rises, less computational resources become available, necessitating a lower cluster size to keep the delay-induced channel mismatch at a minimum.

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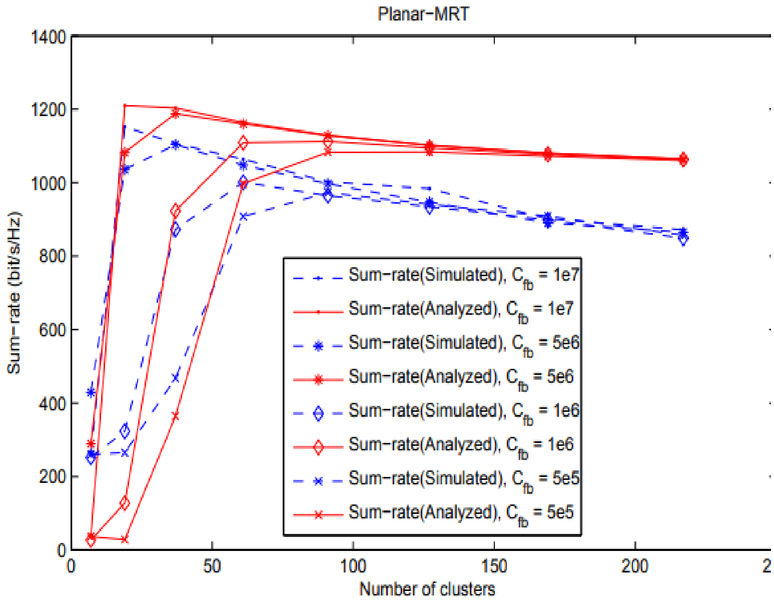

Fig5. No.of clusters vs sum rate

MRT-based precoding, with a low precoding matrix calculation time. In terms of processing time, the curve slopes get more flat as the number of clusters increases. This is because feedback- caused latency is only in the second order of the number of cooperative antennas, whereas processing-caused latency is in the cubic order of the number of cooperative antennas, hence reducing cluster size will result in a faster reduction of delay.

S. No	Parameter	Existing Method	Proposed Method
1	Throughput	16	18
2	Packet Loss	98	60
3	No.of Clusters	50	71

CONCLUSION

This paper proposed an approach for cluster size optimization in cloud-based distributed cooperative small cell networks in the presence of CSI latency, which is primarily caused by cloud processing delay and CSI feedback delay[4]. It was based on commonly used linear precoding algorithms (ZF and MRT) and linear and planar small cell deployment configurations. In the aforementioned framework, an optimization problem is stated, and the desired signal and interference signal are computed, followed by the derivation of the output SINR while accounting for the channel mismatch caused by latency owing to small cell cooperation.

Both delay and output SINR have been calculated as a function of cooperative cluster size, and an optimization problem for maximising network sum-rate has been constructed to trade off interference and channel mismatch. The suggested concise analytical approach may be safely utilised to find the ideal cluster size for every specific deployment, as simulations demonstrate a tiny gap with

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the analytical conclusions in terms of SINR and sum-rate evaluations.

FUTURE SCOPE

Component data consolidation, embedded sensors, IoT devices, and machine-to-machine communication techniques are all examples of CAN-BUS uses in continuing autonomous vehicle development research. Local-to-cloud data transmission, autonomous swarm vehicle management, and improved cyber security procedures are examples of future technologies that could benefit CAN-BUS technology. Despite the fact that controller area networks have bandwidth and latency restrictions, they still serve as useful inputs to more advanced vehicle systems and sophisticated remote networks. CAN-BUS technologies have certainly not reached their full potential, and they will continue to play a key part in the improvement of agricultural technology and farming techniques.

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