Cluster-Based Blockchain Systems for Multi-Access Edge Computing

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Abstract. The computing power and storage requirements of the Internet of Things (IoT) are likely to increase substantially in the future years. Because of the rapid development of both machine learning (ML) and the Internet of Things (IoT), vast volumes of data created by edge devices such as smartphones, laptops, and artificial intelligence (AI) speakers have been widely used to train ML models. In this study, we used a cluster-based Blockchain method in the Multi-Access Edge Computing (MEC, also known as Mobile Edge Computing) for markets and technological services. We describe a generalized stochastic block model (SBM) model for edge computing applications based on the proposed taxonomy. These mobile edge wireless devices (WD) provide efficient resource allocation in mobile network situations.In our studies, we compared the approximate solutions obtained by the SBM to those generated by the cluster-based Blockchain algorithm. However, the high latency and low scalability of traditional blockchain systems limit mobile transactions on the public blockchain. To reduce the consumption of competitive mobile transactions created by linear sequencing blocks, reconstructed blockchain systems have been developed. This study's use of cluster-based blockchain systems provides speedy confirmation and great scalability without significantly compromising security.

Keywords: Machine learning (ML) , cluster-based Blockchain method, Internet of Things (IoT), stochastic block model, Multi-Access Edge Computing (MEC)

1 Introduction

Cluster-based blockchain edge computing is a cutting-edge technology that merges three developing fields: blockchain, edge computing, and cluster computing.Blockchain is a distributed ledger system that enables numerous parties to share a single source of truth without the need for a central authority. Edge computing is a computing paradigm that brings computation and data storage closer to the devices that generate and consume data in order to reduce latency, bandwidth utilization, and reliance on cloud computing. Cluster computing is a technique that allows multiple computers to work together as a cluster to achieve higher performance, availability, and scalability[15]. Cluster-based blockchain edge computing aims to combine the benefits of these three technologies to create a decentralized and efficient computing infrastructure that can support a wide range of applications, from IoT devices to artificial intelligence (AI) algorithms. One potential application of cluster-based blockchain edge computing is in the field of smart cities, where a large number of IoT devices generate data that needs to be processed in real-time. By using a cluster-based blockchain edge computing architecture, smart cities can create a decentralized and secure infrastructure that allows devices to exchange data and compute tasks without relying on a central authority. Another potential application is in the field of AI, where large-scale machine learning models require massive amounts of data and computation. By using a cluster-based blockchain edge computing architecture, AI algorithms can distribute the computation and storage across multiple nodes in a decentralized and fault-tolerant manner, while preserving data privacy and security. This study adopts cluster-based blockchain edge computing, which has the potential to alter the way we build and implement distributed computing systems by providing a flexible, scalable, and secure architecture that can support a wide range of applications and use cases.

Optimally allocating resources in mobile networks is a complex problem that requires balancing the competing demands of various stakeholders, such as users, operators, and service providers. Traditional approaches to resource allocation have relied on centralized control and decision-making, which can be slow, inefficient, and vulnerable to single points of failure. Cluster-based blockchain technology provides a decentralized and secure architecture for managing mobile network resources, making it a possible alternative to traditional resource allocation methodologies. Cluster-based blockchain networks can ensure that resource allocation decisions are made in a distributed and transparent manner without relying on a central authority by employing a blockchain-based consensus process (build an SBM). Mobile network resources can be allocated in a cluster-based blockchain network utilizing smart contracts, which are self-executing computer programs that can autonomously enforce the rules and norms controlling resource allocation. For example, a smart contract could specify the terms of a mobile data plan, such as the amount of data allocated per user, the price of the plan, and the duration of the plan. Cluster-based blockchain networks can also leverage edge computing resources to optimize resource allocation in mobile networks. By using edge computing resources, such as computing power and storage capacity at the network edge, mobile network operators can reduce latency, improve network performance, and enhance the user experience. Overall, cluster-based blockchain technology offers a promising approach to optimally allocating resources in mobile networks. By providing a decentralized and secure infrastructure for managing network resources, cluster-based blockchain networks can enhance network performance, improve user experience, and increase efficiency and transparency in mobile network operations.

Optimally allocating resources in current mobile networks offers three significant issues. Developing strategies for optimal model-based heterogeneous in a 5G and beyond environment based on limited game-based resource allocation schemes.[1]-[3], as well as effective heuristics [6], Machine learning for wireless communications has progressed rapidly since its introduction. In this article, we'll look at three approaches to tailoring deep learning for mobile network applications: mobile data creation, end-to-end Cloud-Edge wireless communications, and network traffic control that can adapt to changing mobile network environments. ,[4]-[5]. A primal-dual approach for learning resource allocations in wireless networks via low-dimensional action utilizing a zeroth-order deterministic two-point gradient approximation scheme;see,e. g.,[7]-[9] space exploration. We analyze the key concerns, techniques, and various state-of-the-art attempts connected to the offloading and task placement QoS Scheduling challenges from a survey-related study. We use a new characterizing network model to investigate the entire job placement offloading policy from mobile devices to the edge cloud.To meet the requirements of practical applications such as robotics and autonomous vehicles, transportation management systems, healthcare, as well as telepresence, virtual reality (VR), augmented reality (AR), and mixed reality (MR), 6G edge computing mobile networks will require massive internet of things connectivity, ultra-reliability, low latency, and extreme high bandwidth.This Fig. 1 edge cloud or edge computing, on the other hand, is a novel concept and technology that can address current cloud computing problems, such as the time it takes to relay information to a centralized data center, which delays decision making. An edge computing solution involves physically relocating computational resources closer to the source of the data, which is typically an IoT device or sensor application.Edge computing removes the need for large amounts of data to be transmitted between servers, clouds, and devices or edge locations to be processed by processing data at the network's edge. Four types of services are deployed from various state-of-the-art MEC, as follows[2]:

- Infrastructure as a service (IaaS) is a type of cloud computing service that offers pay-as-you-go compute, storage, and networking resources on demand. IaaS is one of four types of cloud services, along with software as a service (SaaS), platform as a service (PaaS), and function-as-a-service (serverless).
- Cloud computing services that provide an on-demand environment for designing, testing, delivering, and maintaining software applications are known as platform as a service. PaaS is designed to help developers build web or mobile apps rapidly without having to worry about setting up or managing the underlying infrastructure of servers, storage, networks, and databases.
- Software as a service (SaaS) is a method of delivering software applications internet on demand, typically by subscription. In the case of SaaS, the cloud server and administration of the software application and supporting infrastructure. These servers are also in charge of maintenance tasks including software upgrades and security fixes. Clients gain access to the program over the internet, generally using a web browser on their phone, tablet, or PC.

– FaaS, or Function-as-a-Service, is a cloud computing service that enables clients to execute code in response to events without having to manage the extensive infrastructure that is generally associated with developing and deploying micro-services applications[3].

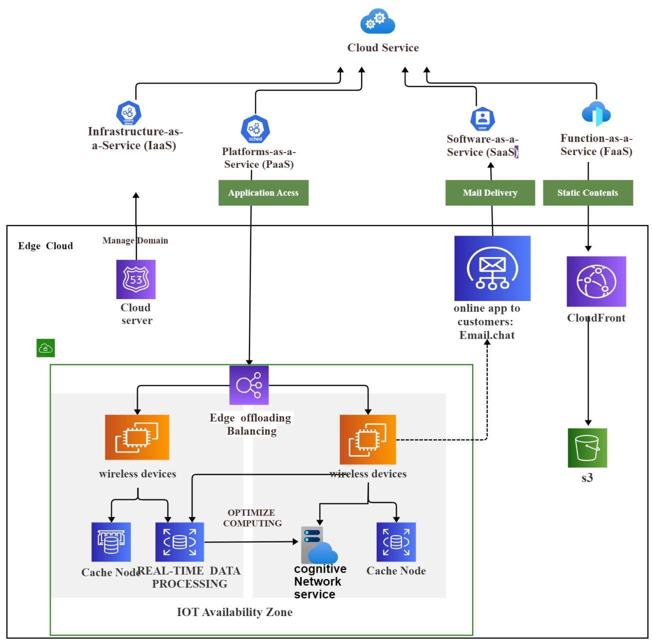

Fig. 1. MEC Infrastructure diagram in 6G network.

The manuscript is organized as follows. Section 2 provides background on MEC optimum resource allocation and the Spectral Graph Theory Concept for Cluster-Based Blockchain Infrastructure. Section 3 presents the design details of Stochastic block model (SBM) for MEC. The prototype implementation and the experimental processing are presented in Section 4, as well as the results and data analysis. Our considerations and future works are listed on Section 5.

2 Spectral Graph Theory Concept for Cluster-Based Blockchain

In this section, we will show how Cluster-Based Blockchain works with associated matrices such as the adjacency matrix and graph Laplacian. Let $G(V, |E|)$ be a graph. We'll let $n = |V|$ denote the number of vertices/mobile nodes, and $m = |E|$ denote the number of edges. We'll assume that vertices are indexed by

$0, \ldots, n-1$, and edges are indexed by $0, \ldots, m-1$. The adjacency matrix**A is a $n \times n$ matrix with $A_{i,j} = 1$ if $(i,j) \in |E|$ is an edge node, and $A_{i,j} = 0$ if $(i,j) \notin |E|$. If G is an undirected graph, then A is symmetric. If G is directed, then A need not be symmetric. The degree of a node i, $deg(i)$ is the number of neighbors of i, meaning the number of edges which i participates in. You can calculate the vector of degrees (a vector d of length n, where $d_i = deg(i)$), using matrix-vector mulpilication:

Lemma 1. *(Matrix-vector multiplication):*
Given a matrix $A \in d_{i \times j}$
vector of degrees: $A \in d_i$
A *and* x *matrix-vector multiplication is defined as*
$d = A\ x$

where x is the vector containing all 1s of length n. You might alternatively simply add the row entries of all matrix A. We will also use $D = diag(d)$ - a diagonal matrix with $D_{i,i} = d_i$. The incidence matrix B is a $n \times m$ matrix which encodes the relationship between edges and vertices. Let $|E|_k = (i,j)$ be an edge. Then the k-th column of B is all zeros except $B_{i,k} = -1$, and $B_{j,k} = +1$ (for undirected graphs, it doesn't matter which of $B_{i,k}$ and $B_{j,k}$ is $+1$ and which is -1 as long as they have opposite signs). Note that B^T acts as a sort of difference operator on functions of vertices, meaning $B^T f$ is a vector of length m which encodes the difference in function value across all edge nodes. You can check that $B^T x_C = 0$, where x_C is a connected component indicator ($x_C[i] = 1$ if $i \in C$, and $x_C[i] = 0$ otherwise). $C \subseteq V$ is a connected component of the graph if all vertices in C have a path between them, and there are no vertices in V that are connected to C which are not in C. This implies $B^T 1 = 0$. The **graph Laplacian** L is an $n \times n$ matrix $L = D - A = BB^T$. If the graph lies on a regular grid, then $L = -\Delta$ up to scaling by a finite difference width h^2, but the graph Laplacian is defined for all graphs. Note that the null-space of L is the same as the null-space of B^T (the span of indicators on connected components). In Fig. 2, it makes sense to store all these matrices in sparse format. Spectral embeddings are one

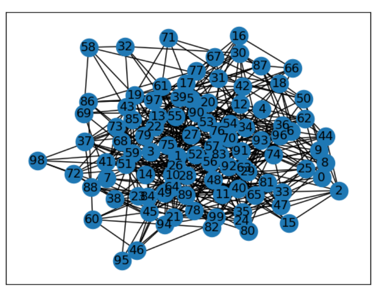

Fig. 2. The graph laplacian of 100 mobile nodes when cluster converge method.

way of obtaining locations of vertices of a graph for visualization. One way is to pretend that all edges are Hooke's law springs, and to minimize the potential energy of a configuration of vertex locations subject to the constraint that we can't have all points in the same location. In one dimension:

$$\underset{x}{\text{minimize}} \sum_{(i,j)\in|E|} (x_i - x_j)^2$$
$$\texttt{subject to}$$
$$x^T 1 = 0, \|x\|_2 = 1$$

Note that the objective function is a quadratic form on the embedding vector x:

$$\sum_{(i,j)\in|E|} (x_i - x_j)^2 = x^T BB^T x = x^T Lx \tag{1}$$

Because the vector 1 is in the nullspace of L, this is similar to locating the eigenvector with the *second-smallest* eigenvalue. We can use the eigenvectors for the next-largest eigenvalues for a higher-dimensional embedding. Spectral Graph Theory is the study of graphs, which are mathematical structures used to model relationships between objects. Spectral Graph Theory focuses on the eigenvalues and eigenvectors of the graph's adjacency matrix, which can provide insight into the graph's properties. For example, spectral graph theory can be used to analyze the connectivity and clustering of a graph.Spectral clustering refers to using a spectral embedding to cluster nodes in a graph. Let A,B⊂V with $A \cap B = \phi$ We will denote

$$E(A, B) = \{(i, j) \in |E| \mid i \in A, j \in B\} \tag{2}$$

One way to try to find clusters is to attempt to find a set of nodes $S \subset V$ with $\bar{S} = V \setminus S$, so that we minimize the cut objective

$$C(S) = \frac{|E(S, \bar{S})|}{\min\{|S|, |\bar{S}|\}} \tag{3}$$

The inequality bounds the second-smallest eigenvalue of L in terms of the optimal value of $C(S)$. In fact, the way to construct a partition of the graph which is close to the optimal clustering minimizing $C(S)$ is to look at the eigenvector x associated with the second smallest eigenvalue, and let $S = \{i \in V \mid x_i < 0\}$. As Fig. 3, let's look at a graph generated by a stochastic block model with two clusters. The "ground-truth" clusters are the ground-truth communities in the model. As Fig. 4,we obtained. A value of 1 means that we found the true clusters.

3 Stochastic block model (SBM) and Cluster-Based Blockchain

This study's SBM structure is a mathematical model used for assessing network structure and community detection, whereas a cluster-based blockchain is a concept that combines clustering with blockchain technology to improve scalability

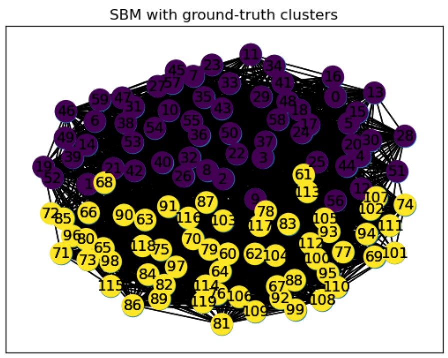

Fig. 3. The graph Laplacian of 100 mobile nodes when spectral clustering to partition into two clusters converge method.

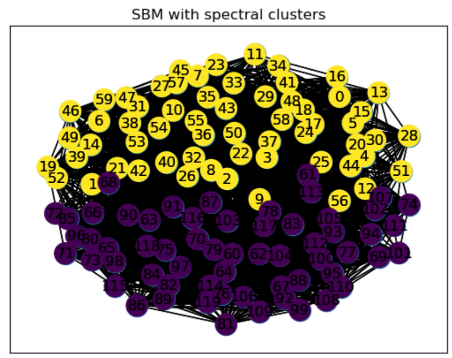

Fig. 4. The graph Laplacian of 100 mobile nodes when the adjusted rand index to measure the quality of the clustering.

and efficiency. It is assumed that nodes in a mobile network are organized into groups or communities, and that edges between nodes are formed based on probabilities that rely on the nodes' community assignments. Assume the following assumptions here: n - the number of mobile nodes in the graph N - $n \times n$ adjacency matrix A - $n \times n$ matrix of probabilities Many statistical network models lie under the umbrella of independent edge random networks, also referred to as the Inhomogeneous Erdos-Renyi (IER) model. The elements of the network's adjacency matrix A are sampled individually from a Bernoulli distribution in this model:

$$A_(i,j) \approx \ Bernoulli(P_{i,j}) \tag{4}$$

If n is the number of mobile nodes, the matrix P is a n*n matrix of probabilities with elements in [0.1] . We can design a variety of specialized models depending on how the matrix P is created. We will now go over a few of these options. It is worth noting that for each model, we assume that there are no loops, or that the diagonal of the matrix P is always set to zero. Each node in the stochastic block model (SBM) is modeled as belonging to a block(sometimes called a community or group). The probability of node i connecting to node j is just a function of the two mobile nodes' block membership. Let n be the number of nodes in the graph, then τ is a length n vector which indicates the block membership of each node in the graph. Let K be the number of blocks, then B is a $K \times K$ matrix of block-block connection probabilities.

$$P_(i,j) = B_{\tau_i \tau_j} \tag{5}$$

In the stochastic block model (abbreviated SBM), we have graphs of the form $G(n, p, q)$. For clarity, consider the following:

Assumption 1 *The class $\mathcal{C}$ is not empty.*
let's assume that n is even and $p > q$

In this paradigm, there are two "communities" of varying sizes $n/2$ so that the probability of an edge existing between any two nodes within a community is p and the probability of an edge between the two communities is q This recovers the communities from a random graph realization $G(V, |E|)$.

The Inhomogeneous Erdos-Renyi model is very simple and lacks many of the properties of networks in real scenarios. It is only a mathematical object with similar phase transition effects. In this study, no communities establish between nodes. An SBM computing for cluster-based blockchain was developed in this study; the majority of these scenarios' MEC models use its variants. Each node in its most mobile nodes belongs to one of C communities, and the occurrence of an edge between two nodes is an event that is independent of the other edges and the probability $\mathbf{Q}_{c_i,c_j}$ (with$\mathbf{Q} \in R^{C\times C}$ definite probability matrix and c_i,c_j node communities i,j respectively).

A graph containing two communities is created by the following cell. Although nodes within the same community have strong connections, nodes within different communities have less connections. Experiment with the two accessible parameters here: 'n' and 'Q'.

This research analyses the qualitative difference between Q with all positive eigenvalues with Q with some negative eigenvalues using two communities to simplify the visualisation. For example, consider the following parameters: 'n=[45, 5, 45, 5]' and $Q = \begin{pmatrix} 0.05 & 0.9 & 0 & 0 \\ 0.9 & 0.8 & 0 & 0.5 \\ 0 & 0 & 0.05 & 0.9 \\ 0 & 0.5 & 0.9 & 0.9 \end{pmatrix}$. How many communities are there about $SBM_n(z, B)$. We know from the graphs that nodes $(0, \frac{n}{2} - 1)$ belong to community A, whereas nodes $(\frac{n}{2} - 1, n)$ belong to community B.

Corollary 1. *Let $p = \alpha \log(n)/n$*
and $q = \beta \log(n)/n$
If:
simulate the probability of exact recovery when

$$\frac{\alpha + \beta}{2} - \sqrt{\alpha\beta} > 1$$

then do the same for

$$\frac{\alpha + \beta}{2} - \sqrt{\alpha\beta} < 1 \tag{6}$$

4 RESULTS AND DISCUSSION

Fig.5 depicts the adjacency matrix for the example, where black and white indicate 1 and 0, respectively. Graphs with binary adjacency matrices are referred to as binary graphs from now on. In the SBM, Fig.7,n=1000 and each node belongs to one of the $K(< n)$ groups, where K = 2 in the example. Because the groups are unknown before to modelling, a K-vector Z_p is also defined for node $p = 1, 2, \ldots, n$, with all elements 0 except one that takes the value 1 and reflects the group node p belongs to in SBM(z, B). In Fig.7 network with ‘n=[60,60] nodes and block matrix use the following parameters‘ $Q = \left(\begin{smallmatrix} 0.5 & 0.2 \\ 0.2 & 0.5 \end{smallmatrix}\right)$. In order to describe the generation of the edges of G according to the groups the nodes belong to, a 2×2 cluster block matrix, denoted by C, is introduced. If Fig.6 G is k-means clustering-based blockchain , for $1 \leq i \leq j \ll K, C_{ij} \epsilon [0, 1]$ and represents the probability of occurrence of an edge between a node in group i and a node in group j. Spectral Graph Theory can be used to analyze the structure of blockchain networks, and to identify nodes that are particularly important for maintaining the network's integrity. Edge computing can be used to improve the performance of blockchain networks by reducing the amount of data that needs to be transmitted over the network. Additionally, edge computing can be used to perform computations related to Spectral Graph Theory, such as the calculation of graph Laplacians, which can be useful for machine learning and other applications.Let p be denote the probability of an edge between nodes in the same cluster, and q denote the probability of an edge between nodes in different clusters. This Study consider Spectral Graph Theory for stochastic block model with $k = 2$ clusters and $n = [60, 60]$ nodes per cluster.Fig.8 Analysis Adjacency spectral embedding when mobile nodes Histogram and Fig.9 scatter diagram for 2 communities distribution state. Plot a phase diagram of the adjusted rand index (ARI) score as p and q both vary in the range $[0, 1]$ The Random Dot Product Graph (RDPG) can also be applied in the context of blockchain analysis or modeling. In this study, the RDPG can be used to represent relationships or interactions between different entities in a blockchain network. A blockchain is a distributed ledger that records transactions across multiple nodes or participants. Each transaction can involve different entities such as users, addresses, or smart contracts. By representing these entities as nodes and their interactions as edges in a graph, the RDPG can help capture and predict analyze the underlying structure and dynamics of the blockchain network. To construct an RDPG for blockchain analysis, one can associate latent vectors or features with each entity in the blockchain. These latent vectors can represent various characteristics or attributes of the entities, such as transaction history, account balances, or network behaviors. In Fig.10, the dot product of the latent vectors of $k = 5$ clusters under pairwise distance entities can then be utilized to determine the likelihood of an interaction or connection between them.If the dot product, for example, exceeds a specific threshold, an edge can be constructed between the respective nodes in the RDPG. After constructing the RDPG, several graph analysis techniques can be used to acquire insights into the blockchain network. In Fig.11 $k = 6$ clusters, RDPG can incorporate community discovery, centrality metrics, clustering, and anomaly detection, among other things. Using the RDPG framework, researchers and predictive analysts can investigate the structural characteristics and behaviors of the blockchain network and perhaps find patterns or anomalies that may be useful for understanding its dynamics or detecting fraudulent activity. It is crucial to note that the application of the RDPG to blockchain analysis is still an evolving MEC scenario, and there are numerous computers and methodologies that can be applied depending on the specific cloud edge computing for vehicle and transport.

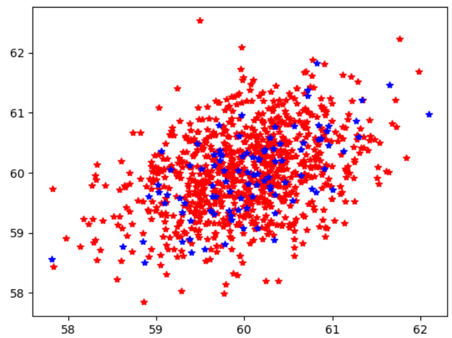

Fig. 5. The graph execution time and energy consumption of each mobile nodes when cluster converge method..

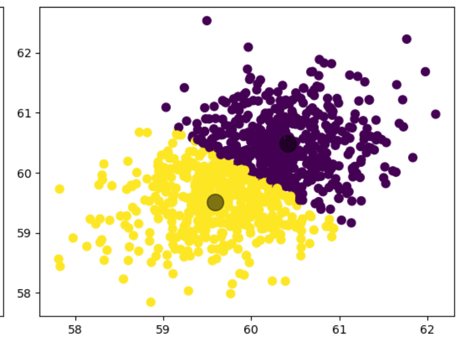

Fig. 6. The graph execution time and energy consumption of each mobile nodes when kmean cluster method..

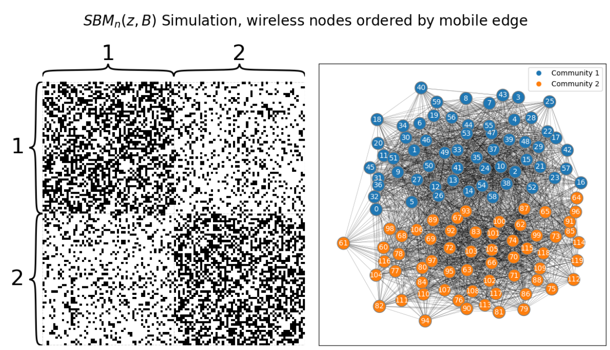

Fig. 7. The graph execution time and energy consumption of each mobile nodes when stochastic Block Model method.

5 Conclusion and future work

This investigation Multi-Access edge computing assisted wireless device (IoT) offloading scheme communications is a key component of the future 6G scenario. In this paper, we offer a new SBM-based method for cluster-based Blockchain optimization of transmit reinforcement and resource estimation in a 6G communication system. The technique used by the MEC system while also meeting

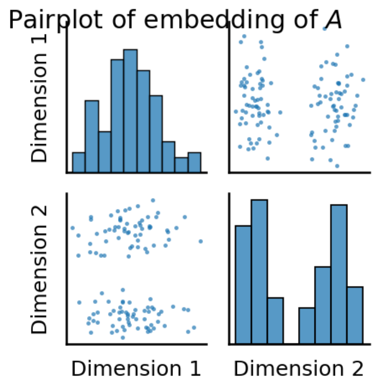

Fig. 8. Analysis Adjacency spectral embedding when mobile nodes Histogram for 2 communities.

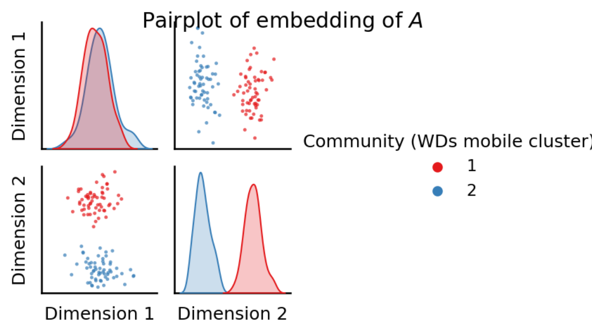

Fig. 9. Analysis Adjacency spectral embedding when mobile nodes scatter diagram for 2 communities.

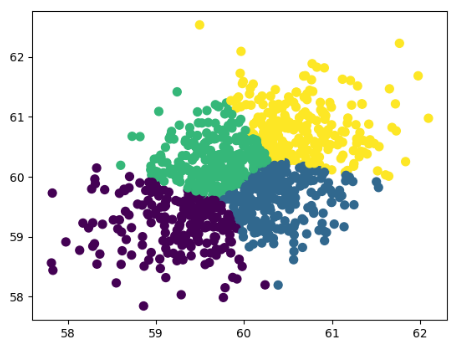

Fig. 10. The graph execution time and energy consumption of each mobile nodes when pairwise distance mode.

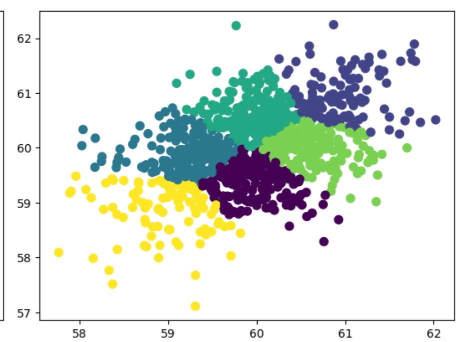

Fig. 11. The graph execution time and energy consumption of each mobile nodes when predict method.

the greatest transmit power restriction. The simulation results suggest that the proposed offloading technique can reduce the cumulative rate of MEC communication in a short period of task time (CPU time) when compared to the real-world scheme with fixed transmit mobile cloud computing. In the future, we will examine optimal allocation of MEC to IOT using a matching algorithm, as well as deep learning-based design of a 6G cloud integration environment.

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