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Flexible Virtual Cell Design for Ultradense Networks: A Machine Learning Approach

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ABSTRACT With the ever-growing demand for even higher throughput, ultradense networks (UDNs) are being deployed for the fifth generation (5G) mobile communications. Although massively distributed radio access points (APs) result in a considerable increase in throughput, they also cause some critical problems. When employing a wireless backhaul, the backhaul capacity becomes a limiting factor, which may result in a high packet loss rate. Furthermore, dense deployment of APs leads to more frequent handoffs for mobile user equipment, which results in heavy measurement and signaling overhead. For a better trade-off between the packet loss rate and the handoff overhead, a machine learning approach for flexible virtual cell (VC) design is proposed that leverages particle swarm optimization (PSO) to quickly find the optimal VC solution. To be responsive to the dynamic traffic demand and backhaul capacity of APs, a new parameter called "weighted distance" is employed in the modified K-means algorithm, which is nested in the PSO procedures for master AP selection and VC boundary determination. Compared with an exhaustive search, optimal VC solutions can be found efficiently through considerably fewer iterations. The proposed method is generic and applicable to disparate UDN application scenarios.

INDEX TERMS K-means clustering, mobility management, particle swarm optimization, resource management, ultradense networks, virtual cell.

I. INTRODUCTION

WITH the explosive growth of mobile traffic during recent decades, the fifth generation (5G) mobile communication system is in the stage of standardization and commercial deployment. Throughput, spectral and energy efficiency, reliability, and latency are the key driving forces when offering various user-centric 5G services. To satisfy these requirements, the ultradense network (UDN) has been regarded as one of the most critical technologies for 5G [1], [2]. By introducing low-power and low-cost radio access nodes, the density of radio access points (APs) increase greatly in UDN. Thus, spectral efficiency is dramatically improved. Moreover, the densely deployed network faces many new challenges, which can be categorized into five key issues: flexible architecture, mobility management, resource management, interference management, and security management [1], [3].

The proposed flexible virtual cell (VC) design aims to solve the following two problems. The first problem is to reduce the handoff overhead through mobility management. Unlike traditional cellular networks, APs in UDN deploy randomly and densely. The distance between two neighboring APs can be as close as 10 m to offer seamless connections, while the density of APs is comparable to the density of user equipment (UE). The irregular deployment of APs is mainly due to practical limitations of infrastructure deployment and the opportunistic introduction of low-cost APs [2]. Mobile UEs such as vehicular transceivers or mobile phones on a vehicle are faced with unprecedented and frequent handoffs, which may cause undesired heavy measurement and signaling overhead. Moreover, the allowed handoff execution time decreases significantly.

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If handoff procedures are not properly designed, then UE mobility will face an intolerable handoff failure rate. Thus, mobility management is of crucial importance.

The second problem is to maximize the network capacity with wireless backhaul constraints through resource management. To satisfy the UE's demand for quality of service (QoS) no matter where it is located, user-centric service is efficient when allowing access to multiple APs [4]. However, due to the rapid increase of the AP density and different QoS requirements for UEs, it is a complex task to allocate radio resources such as bandwidth and time slots. Moreover, prediction of incoming traffic and load balancing among APs for context-aware resource allocation are challenging. In addition to the problems above, low cost is yet another vital goal. For some scenarios, it is economically impractical to deploy wired backhaul for every AP. Therefore, capacity-limited wireless backhaul may be employed to complement the wired backhaul. In a typical scenario, APs are supported with appropriate backhaul that can optimize jointly from the topology, bandwidth, and power aspects [5].

In this article, in addition to inter-cell interference, both handoff overhead and backhaul capacity are taken into consideration when forming VCs. VC formation is the process of spectrum allocation, as all APs in the same VC share the same channel(s). For the proposed flexible VC design, the master AP, which manages the backhaul of all user data within the VC and monitors inter-VC handoffs, needs to be dynamically selected. Generally, the master AP is located near the center of the slave APs. Therefore, each VC can be regarded as a cluster that contains a master AP and several slave APs. At the same time, the VC design can be considered as a clustering problem with multiple constraints. An optimal VC design scheme needs to trade off the packet loss rate and inter-VC handoff overhead. As can be seen from Fig. 1, if the coverage of a VC is too extensive, then the demand for backhaul within the VC may exceed the backhaul capacity of the master AP, causing a high packet loss rate. When the total required throughput exceeds the backhaul capacity of the master AP, the packet loss rate of the associated VC will deteriorate. In addition, if the VC is too small, then a mobile UE will face frequent handoffs between VCs. An inter-VC handoff is triggered when the VC with which a UE is associated is changed. When the whole region confronts high mobility, heavy inter-VC handoff overhead will occur. Hence, the coverage of each VC cannot be too large or too small when backhaul constraint and inter-VC handoff overhead are jointly taken into consideration.

To address the problems above, the number of VCs, which corresponds to the optimal VC solution, needs to be determined by a clustering algorithm. In the traditional approach, an exhaustive search is used to calculate the performance with a different number of clusters, but this tends to be inefficient. Instead, particle swarm optimization (PSO) is used. This is a distributed artificial intelligence (AI) algorithm that can be implemented by parallelizing the operation of each particle. It is more efficient than an exhaustive search. K-means is a classic clustering method with the advantages of simplicity and high efficiency. Considering the limitation of the backhaul capacity, it may lead to a high packet loss rate. Therefore, we define the "weighted distance" and propose a weighted-distance-based K-means. The main contributions of this article are summarized as follows.

- We expose the main challenges that arise in VC design suitable for various UDN application scenarios. Then, we present a machine-learning-based approach for flexible VC design. It can be employed to find the optimal number of clusters and VC boundary to better trade off the handoff overhead and packet loss rate.
- We define a new parameter termed "weighted distance" by considering the backhaul capacity. It is proven in this article that network performance is enhanced when the weighted distance replaces the actual distance in K-means.
- We leverage PSO and modified K-means clustering to dynamically change the coverage of VCs to adapt to varying traffic requirements and backhaul constraints in scenarios with mobile UEs. This is more generic and applicable to various UDN application scenarios.

The rest of this article is organized as follows: We review the related work in Section II. The system model is presented in Section III. We discuss the proposed machine-learning-based flexible VC design procedures in detail in Section IV. After that, the performance of the proposed VC design scheme and simulation results are given in Section V. Finally, Section VI concludes this article.

II. RELATED WORKS

From the perspective of mobility management, cell virtualization can be an attractive approach to dealing with mobility problems. In [6], a VC-based mobility enhancement design was proposed to offer seamless coverage and improve handoff performance. In this article, a VC is dynamically formed with multiple APs that cooperatively serve a UE. However, the VC forming or reforming procedure involves high complexity and a large number of UEs. Therefore, another VC design for seamless connectivity and senseless moving was proposed in [7]. This is a local-anchor-based architecture that contains a static cluster of APs. UEs within a VC can select multiple serving APs according to their different channel conditions. The local anchor takes the responsibility of managing the backhaul of all user data within the VC as well as handoffs for UEs within the

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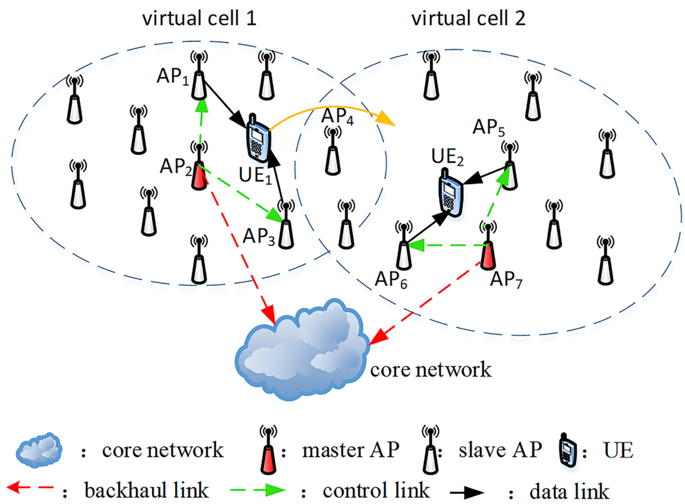

FIGURE 1. System model.

same VC or between different VCs. In this work, the backhaul between the local anchor and the core network is assumed to be ideal (i.e., the backhaul capacity is unlimited), and only static VC is considered for hot-spot application scenarios such as highly dense business or residential buildings. Although the formation of VC is simplified, the VC may not be flexible enough to accommodate the dynamic traffic requirements of mobile UEs.

As the most important branch of AI, machine learning (ML) has great potential to solve these complicated problems in UDN. Recently, ML-based algorithms were proposed for resource management and mobility management. The extracted information can be used to build an efficient decision-making system by using ML algorithms, which helps to explore regularities in complicated wireless environments such as UDNs [8]. For example, by employing deep reinforcement learning (DRL), a method that can achieve a trade-off between spectrum efficiency, energy efficiency, and fairness was proposed for resource allocation in UDN. Furthermore, it significantly outperformed traditional algorithms [9]. Cluster-based resource management issues in UDN have been studied extensively. For example, in [10], the authors introduced a clustering-based resource allocation framework for downlink transmission in UDN to address the challenges of large communication overhead and inter-cluster interference. In addition, a hierarchical resource allocation framework was proposed in [11] to include four stages: clustering, intra-cluster subchannel allocation, inter-cluster collision resolution, and power adjustment. This was verified to achieve satisfactory system performance with a faster convergence speed. Similarly, a cluster-based energy-efficient resource allocation scheme was proposed to mitigate the interference and boost energy efficiency in UDN [12]. Instead of employing a predetermined fixed number of clusters, a modified K-means algorithm was utilized in the BS clustering process to dynamically adjust the number of BS clusters according to the BS density [12].

In [13], the authors presented a comprehensive review of impediments to the wide deployment of UDN. They proposed a software-defined space-air-ground integrated moving cells (SAGECELL) architecture, which is a programmable and flexible framework to integrate space, air, and ground resources for matching dynamic traffic demands with network capacity supplies. It was also envisioned that network function virtualization can be employed to create VC in SAGECELL [13]. However, it should be noted that the realization of SAGECELL heavily relied on not only the ultradense deployment of moving cells but also efficient resource sharing of different types of network elements among multiple operators or parties.

To satisfy the demanding requirements of 5G communications, cognitive radio (CR)-based dynamic spectrum access (DSA) has been widely investigated as an important enabling technology. In DSA systems, secondary users (SU) may access the spectrum of licensed primary users (PU) opportunistically on a non-interference basis. For 5G networks, multi-tier or hierarchical spectrum access systems (SAS) with different priorities and QoS requirements were proposed in which each tier has different QoS requirements [14]. As an example, the U.S. President's Council of Advisors on Science and Technology (PCAST) recommended a three-tier hierarchy (i.e., federal primary access, priority secondary access, and general authorized access) for access to the federal spectrum [15]. In this three-tier architecture, the first-tier users are entitled to interference protection to a level such that their communication performance requirements are satisfied. The second-tier users receive short-term priority authorizations, while third-tier users are entitled to use the spectrum on an opportunistic basis and are not entitled to interference protection. In the U.S., the FCC proposed a dynamic spectrum management framework for the Citizen Broadband Radio Service (CBRS) governed by SAS [16]. However, the spectrum allocation in the current 3.5 GHz CBRS standard only considers co-channel interference from neighboring cells.

Different from the related works above, we propose a method to find an optimal VC solution and select the master AP by leveraging PSO and weighted distance-based K-means. Instead of an exhaustive search, PSO is used to reduce the search time, in which modified K-means is executed for every iteration. Moreover, in our proposed algorithms, network fitness is defined to better trade off the packet loss rate and the handoff overhead.

III. SYSTEM MODEL

Since small cells are currently widely deployed, we focus on resource management and mobility management in a single-tier UDN with an architecture of small cells. Fig. 1 shows the system model. We consider a single-tier UDN with a large number of APs distributed in a region following the hard core point process (HCPP), in which no two points of the process coexist with a separating distance shorter than a predefined hard core parameter r_h [17]. UEs are randomly distributed with different demands on backhaul and mobility trajectories. The set of all APs is denoted as $C = \{1, 2, ..., M\}$, where M is the total number of APs. A VC is a cluster of APs that contains a master AP and several slave APs. To make the VC design more practical, the backhaul between the core network and APs is assumed to be wireless with limited capacity. The coverage of VC dynamically changes to adapt to different traffic requirements and user mobility scenarios.

We consider the packet loss rate and number of inter-VC handoffs as the network performance indicators. Packet loss occurs when the throughput requirements exceed the backhaul capacity, so the packet loss rate in the n-th VC (P_n) is estimated by

$$P_n = \begin{cases} \frac{R_n^{sum} - C_n}{R_n^{sum}}, & R_n^{sum} > C_n \\ 0, & R_n^{sum} \leq C_n \end{cases} \quad (1)$$

where R_n^{sum} is the sum throughput demand from all UEs in the n-th VC, and C_n is the backhaul capacity of the master AP in the n-th VC. Inter-VC handoffs occur when the moving UEs pass through the VCs.

Modified hyperbolic tangent functions (i.e., f-function) can be employed to evaluate network performance and can accommodate a large range of performance variations and capture the value of the service to the user quite naturally [18]. The f-function can be written as

$$f_i(x, x_0) = \frac{1}{2}\{\tanh[\sigma_i(\eta_i - x/x_0)]+1\} \quad (2)$$

where x and x_0 are the performance metric and its target value, respectively; σ_i (i = 1, 2) is a spread parameter; and η_i (i = 1, 2) is threshold of x/x_0.

When considering the packet loss rate, P_n is actually x/x_0. Then, the fitness of the n-th VC can be calculated by

$$f_1(P_n) = \frac{1}{2}\{\tanh[\sigma_1(\eta_1 - P_n)] + 1\} \quad (3)$$

where σ_1 is a spread parameter, and η_1 is threshold of P_n. If the estimated packet loss rate surpasses the packet loss threshold that the network can tolerate, then the corresponding fitness drops quickly close to zero. Furthermore, the fitness of the average packet loss rate is estimated by

$$U_{pl} = \frac{1}{K}\sum_{n=1}^{K} f_1(P_n) \quad (4)$$

where K denotes the number of VCs.

For a feasible VC scheme, the number of boundary crossings made by mobile UEs (i.e., H_o) is estimated based on the instantaneous velocity of UEs and the geographical information (e.g., a street map). Generally, a handoff threshold (H_{th}) is defined according to the capability of the networks to deal with inter-VC handoffs. Similarly, the fitness accounting for inter-VC handoff can be calculated by

$$f_2(H_o, H_{th}) = \frac{1}{2}\{\tanh[\sigma_2(\eta_2 - H_o/H_{th})] + 1\} \quad (5)$$

where σ_2 is a spread parameter, and η_2 is the threshold of H_o/H_{th}. If the estimated total number of handoffs exceeds the handoff threshold, then the corresponding fitness value becomes extremely small.

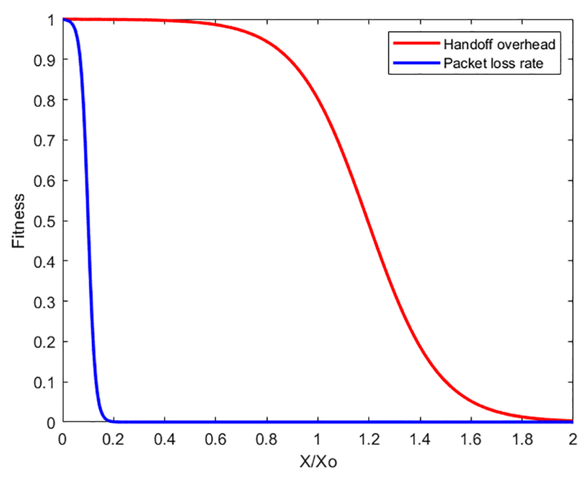

FIGURE 2. Fitness function corresponding to packet loss rate vs. handoff overhead.

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The fitness function corresponding to the packet loss rate vs. handoff overhead decreases according to the trend shown in Fig. 2. When x/x_o equals the threshold (η_i), the fitness is 0.5. Spread parameter (σ_i) determines the decline rate of fitness. The larger the parameters, the faster the fitness decreases.

To better trade off the packet loss rate and inter-VC handoffs, the network fitness (U_{net}) is introduced. The network fitness of a VC design scheme is calculated by jointly considering backhaul constraints and the estimated inter-VC handoff overhead, and indicates how well a solution balances the packet loss rate and handoff overhead. It is calculated by

$$U_{net} = \alpha \frac{1}{K} \sum_{n=1}^{K} f_1(P_n) + \beta f_2(H_o, H_{th}) \tag{6}$$

which is a weighted combination of two parts, namely, the average utility of all VCs in the network according to the estimated packet loss rate in each VC and the system overhead according to the number of estimated inter-VC handoffs (H_o). Note that the sum of two weights equals 1 (i.e., $\alpha + \beta = 1$). Therefore, the process of finding the optimal VC design is actually the process of optimizing the network fitness.

IV. PROPOSED VC DESIGN

In this section, an ML-based flexible VC design approach is detailed that aims to enable scenario-aware flexible VC design while taking related factors such as traffic demand, packet loss rate, and handoff overhead into consideration. The flexible VC design scheme is adaptable to dynamic traffic requirements, mobility scenarios, and different network topologies.

The VC design consists of two interlocking procedures: determination of the number of VCs for the given scenario and boundary determination for all VCs, and selection of the master AP for each VC. Obviously, it is difficult to know beforehand into how many VCs the whole region should be divided, and what the coverage of each VC should be. As a design criterion, if a region features high user mobility and a light burden on backhaul, then the coverage of VC is preferred to be large. Otherwise, if a region features low user mobility and a heavy burden on backhaul, then the VC coverage tends to be small. In other circumstances, these two key factors need to be carefully weighed. As a prior estimation of inter-VC handoff overhead is needed in order to evaluate the performance of the VC design, the VC boundary needs to be determined before estimating the number of handoffs for a candidate VC scheme.

In this article, the proposed VC design algorithm leverages PSO and the modified K-means clustering algorithm to solve the above-mentioned problems. Each particle executes a modified K-means to find the optimal AP clustering under a certain number of VCs. In order to evaluate the performance of the scheme given by the modified K-means, the corresponding VC boundary is generated by employing Voronoi tessellation. Multiple particles run in parallel to find the optimal number of VCs and the corresponding VC design scheme. Next, the detailed design of PSO and the modified K-means algorithms are discussed.

A. FINDING OPTIMAL NUMBER OF VCS

For different user traffic distributions, user mobility patterns, and AP distribution scenarios, the optimal number of VCs can be as large as the total number of APs or as small as one. When there is a great number of APs, it is highly inefficient to search for every possible number of VCs and the corresponding optimal coverage of each VC exhaustively. Thus, PSO is employed to speed up the search process. The optimization process is executed by particles distributed randomly in the search space. Multiple particles that form a population move in the search space for the best solution. A particle is an independent agent that can combine the experience of itself with its companions.

The search space spans 1 to M. In each iteration, all particles will move toward better positions by adjusting two key parameters: velocity and position. The velocity of a particle determines the direction and the step size it will choose. The position of each particle is updated according to the updated velocity. The position of a particle represents the number of VCs. Therefore, the velocity and position are both integers, which are updated by

$$v_i^{k+1} = v_i^k + \langle \phi_1 r_1 (gbest^k - y_i^k) + \phi_2 r_2 (pbest_i^k - y_i^k) \rangle \tag{7}$$

$$y_i^{k+1} = y_i^k + v_i^{k+1} \tag{8}$$

where v_i^{k+1} and v_i^k represent the current and previous velocities of the i-th particle, respectively; y_i^{k+1} and y_i^k are the current and previous positions of the i-th particle, respectively; ϕ_1 and ϕ_2 are acceleration factors; r_1 and r_2 are random numbers between $[0, 1]$; $pbest_i$ is the best fitness of the i-th particle; $gbest$ is the global best fitness; and $\langle\cdot\rangle$ means to round the value.

Maximum and minimum values are set for velocity and position. When the value exceeds the maximum, it will equal the maximum. The same occurs when the value is less than the minimum.

Each particle can turn toward a better position in each iteration because there are two important parameters: $pbest$ and $gbest$. In each iteration, every particle updates the best position and the corresponding best fitness $pbest$ throughout the current iteration. The global best fitness $gbest$ is updated and shared among all particles. Particles update their positions according to the respective best fitness and global fitness. The process of searching for $gbest$ is the process of searching for the optimal network fitness. The entire search process stops when the network fitness converges or the number of iterations reaches maximum. The major pseudocode of the PSO procedure is shown in Algorithm 1 below.

Algorithm 1 Finding Optimal VC Solution by PSO

Randomly select N_p different locations from [1, M] as initial locations of N_p particles
Initialize $gbest$
for each particle i **do**
  Calculate U_{net} leveraging the modified K-means and VC boundary determined by Voronoi
  Initialize $pbest_i$
end for
repeat
  for each particle i **do**
    Update velocity v_i according to $gbest$ and $pbest_i$
    Update position y_i
    Calculate U_{net}
    Update $pbest_i$
    Update $gbest$ by choosing the particle with the best U_{net}
  end for
until $gbest$ converges or reaches the maximum number of iterations

B. DETERMINING APPROPRIATE BOUNDARY BETWEEN VCS

In order to find an optimal VC design scheme under a certain number of VCs generated by a particle of PSO, the proposed algorithm can be divided into two stages: the AP-clustering stage and the boundary determination stage. We utilize the modified K-means method in the AP-clustering stage by considering the dynamic demand on the backhaul surrounding the AP centroid and the backhaul capacity of the AP centroid. Then, in the second stage, Voronoi is employed to determine the VC boundary and calculate the corresponding network fitness of the generated AP clustering scheme.

For the proposed flexible VC design, we introduce the weighted distance for the modified K-means algorithm, where the weighting factor (w) is set proportionally to the ratio of the AP centroid's backhaul demand to its backhaul capacity limit. For example, the weighting factor for the i-th cluster (w_i), which is calculated when clustering all APs into K clusters, is defined by

$$w_i = \frac{R_i/C_i}{\sum_k^K R_k/C_k} \tag{9}$$

where R_i and C_i denote the backhaul demand surrounding the i-th AP centroid and the backhaul capacity limit of the i-th AP centroid, respectively. Then we can define the weighted distance between the i-th AP centroid and the m-th AP by

$$D_{mi} = w_i d_{mi} \tag{10}$$

where d_{mi} represents the geometrical distance between the i-th AP centroid and the m-th AP. If $D_{mi} < D_{mj}$ is satisfied $\forall j \in [1, K](j \neq i)$, then we tend to add AP_m to the i-th cluster. Therefore, the weighting factor indicates that the higher the backhaul demand on the i-th cluster, the lower probability that AP_m will be added into the i-th cluster. By contrast, the larger the backhaul capacity of the i-th AP centroid, the higher probability that AP_m will be assigned to the i-th cluster. The weighted distance, which considers both the geometric distance and the backhaul demand and capacity, can adapt to the dynamic traffic demand and backhaul capacity of APs.

We use a combination of PSO and modified K-means in which each particle searches for an optimal solution in the updated position through the modified K-means algorithm. Assuming that the updated position of a particle is K in one iteration, we divide all APs in the entire region into K clusters based on the modified K-means algorithm. The modified K-means clustering, which determines the coverage of each VC, jointly considers the user traffic demand on backhaul surrounding the AP centroid and the limited backhaul capacity between the master AP centroid and the core network. Thus, a VC design scheme is formed that can adapt to disparate UE requirement scenarios and AP distribution scenarios. At the beginning of the procedure, we select K APs with a minimum distance longer than r_h^K as initial centroids. To maintain sufficient distance between the initial centroids, r_h^K is defined by

$$r_h^K = r_h \times \sqrt{\frac{M}{K}} \tag{11}$$

where r_h is the minimum distance between APs, M is the number of APs, and K is the number of clusters, which changes dynamically in each iteration. Then, in each iteration, we group APs into a cluster with the minimum weighted distance. In the traditional K-means, the centroid of each cluster is not necessarily a clustering AP. In contrast, in our modified K-means algorithm, we select the AP closest to the geometric center as the new centroid of a cluster in the next iteration. After the algorithm stops iterating, current centroids are selected as master APs of this VC design scheme.

In the next stage, the VC boundary is determined so that we can estimate the inter-VC handoff overhead and average packet loss rate of the network. Due to the spatial randomness distribution of APs and the uncertainty of the number of APs in a VC, the VC boundary is usually irregular. Voronoi is a mathematical tool that can form a planar graph called Voronoi tessellation. It is constructed using perpendicular lines that bisect the

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segment between two points [17]. The VC boundary is determined by Voronoi tessellation. First, Voronoi is employed to generate the boundary of each AP. Each Voronoi cell can be taken as the coverage of each small cell. Second, multiple APs that belong to the same cluster are combined to form the coverage of each VC. In this way, a VC scheme under a certain number of VCs is formed. Finally, U_{net} is calculated by a weighted combination of f_1 and f_2. The pseudocode of modified K-means procedures for master AP selection and VC boundary determination is shown in Algorithm 2 below. The time complexity of the K-means clustering algorithm is $O(KlN)$. In this work, K is the number of clusters, N is the number of APs, and l is the number of iterations of K-means [19]. In our modified K-means algorithm, employment of the weighted distance will not affect the complexity, and K is far lower than N. Therefore, the complexity can reduce to approximately $O(lN)$. Furthermore, the complexity of Algorithm 1 is approximately equal to $O(mlN + mI) \sim O(lN + I)$, where I is the number of iterations of PSO and m is the number of particles, which is far lower than N and I.

Algorithm 2 Selecting Master AP and Determining VC Boundary by Modified K-means

```
Select K APs with a minimum distance greater than r_h^K as initial centroids
repeat
    for each AP m do
        for each cluster i do
            Calculate D_mi
            if D_mi is the minimum weighed distance of AP_m then
                Add AP_m to the i-th cluster
            end if
        end for
    end for
    for each cluster i do
        Select the closest AP to the geometric center as new centroid
    end for
until The positions of cluster centroids stay the same as last iteration
Generate the boundary of the VCs by Voroni
Calculate U_net //, and then update the pbest of each particle in Algorithm 1
```

V. SIMULATION RESULTS

In this section, we evaluated the performance of the proposed VC design algorithm. The simulation parameters are listed in Table I.

As shown in Table I, the simulation area is 1000 m $\times$ 1000 m, in which 100 APs are generated as an HCPP. The minimum distance between APs (r_h) is set to 60 m. The backhaul capability of APs ranges from 30 to 100 Mbps. Two hundred UEs with traffic demands are randomly distributed and move in the simulation area. The velocity of the UEs varies from 0 to 100 km/h. The number of particles in the PSO is 3. The weight for packet loss (α) is 0.6, and the weight for handoff overhead (β) is 0.4 in the simulation. The inter-VC handoff threshold (H_{th}) is set to 60. To verify the advantages of the proposed algorithm implementing PSO nested with modified K-means, an exhaustive search is conducted as a performance comparison. At the same time, to evaluate clustering performance, a direct clustering method is used as a baseline approach for comparison.

TABLE 1. List of Simulation Parameters

Parameter	Value
Simulation area	1000 m $\times$ 1000 m
Number of APs (M)	100
Minimum distance between APs (r_h)	60 m
Backhaul capability of master APs (C_n)	30 – 100 Mbps
Number of particles	3
Number of UEs	200
Velocity of UEs	0 – 100 km/h
Mean of required throughput for UE	5 Mbps
Standard deviation of required throughput for UE	3 Mbps
Minimum required throughput for UE	1 Mbps
Weight for packet loss rate (α)	0.6
Weight for handoff overhead (β)	0.4
Handoff threshold (H_{th})	60
Maximun number of PSO iteration	10
Accelerating factors of PSO (ϕ_1, ϕ_2)	1, 1
Velocity of each particle	$[-8, 8]$
Position of each particle	$[3, 100]$

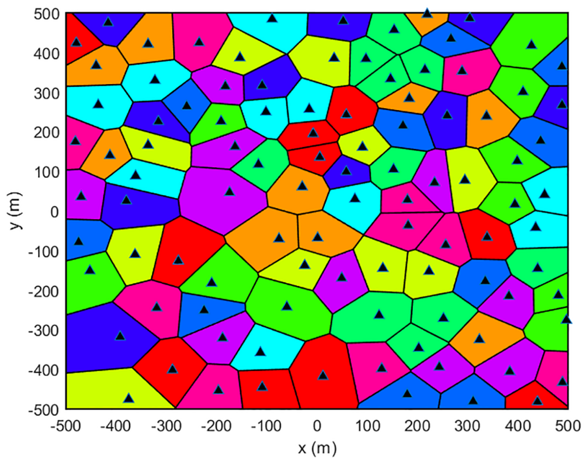

FIGURE 3. Boundary of each AP coverage generated by Voronoi (Note: each triangle represents an AP.).

Fig. 3 shows the initial Voronoi cell. Each triangle represents an AP. When adopting different VC design schemes, various boundaries of VCs are generated.

Fig. 4 and Fig. 5 show the estimated average packet loss rate and total number of inter-VC handoffs of the network when using the exhaustive search, respectively. As expected, when the number of VCs increases, the

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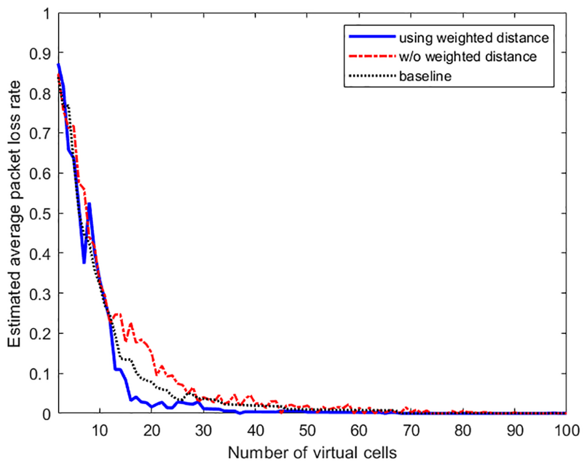

FIGURE 4. Average packet loss rate vs. number of VCs by exhaustive search.

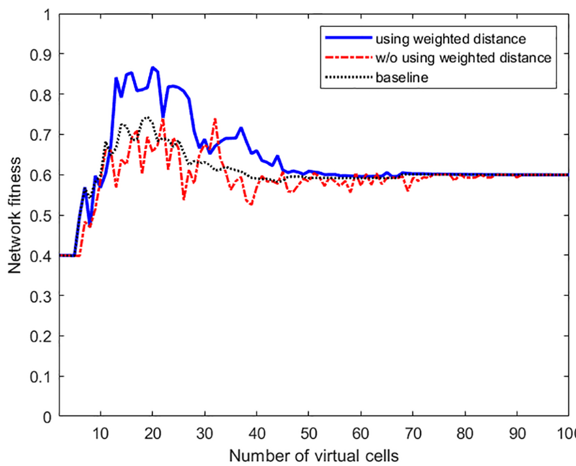

FIGURE 6. Network fitness generated by exhaustive search.

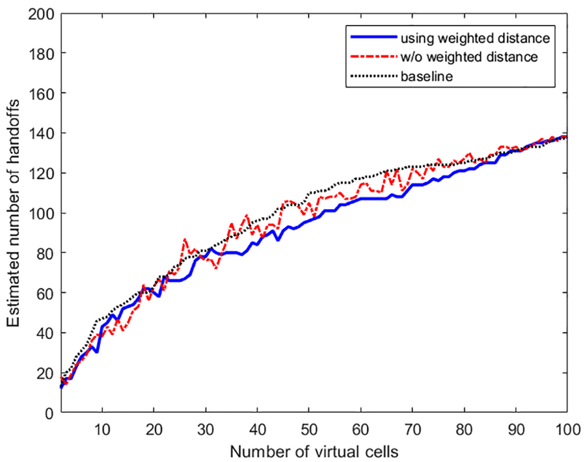

FIGURE 5. Number of inter-VC handoffs vs. number of VCs by exhaustive search.

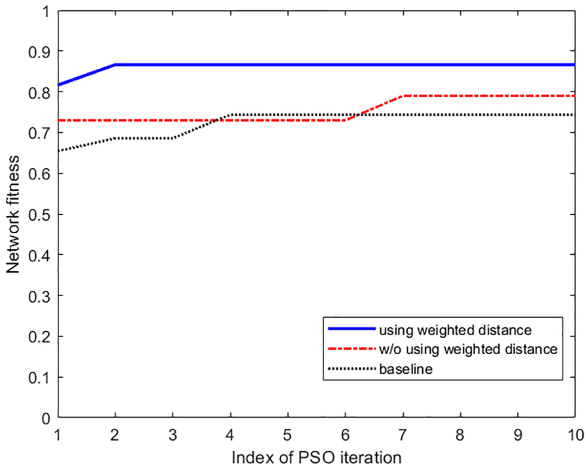

FIGURE 7. Network fitness generated by PSO.

average packet loss rate of the network decreases while the inter-VC handoff overhead increases gradually. As shown in Fig. 4, compared with the traditional K-means and baseline method, the packet loss rate is significantly reduced when using the weighted distance. Furthermore, in Fig. 5, the number of handoffs can be also reduced with proper VC design. This indicates that the weighted distance we proposed is more suitable for wireless backhaul demand and capacity in UDN than the geometric distance.

Fig. 6 shows the network fitness through an exhaustive search, while Fig. 7 shows the network fitness of the optimal scheme found through several rounds of PSO iterations. It can be seen that the proposed PSO algorithm converges within 2 iterations and obtains an optimal network fitness of 0.87. When using the exhaustive search, we also find the optimal network fitness is 0.87. This proves that PSO can find the same optimal network fitness attained by an exhaustive search with a significantly fewer number of iterations. Thus, the proposed algorithm can dramatically speed up the process of searching for the optimal VC design scheme. Moreover, as can be seen from Fig. 6 and Fig. 7, the proposed modified K-means (using weighted distance) algorithm also contributes to an even higher optimal network fitness as compared with the baseline method and the traditional K-means clustering method without using the weighted distance. Therefore, the modified K-means has better clustering performance when considering the backhaul capacity constraint.

The best VC scheme leveraging PSO and modified K-means algorithm is shown in Fig. 8, in which the triangles with the same color belong to the same VC. APs surrounded by circles are selected as master APs by employing the modified K-means, and the number of circles is also the number of optimal VCs. Fig. 9 shows the boundary of the optimal VC scheme, which is the best clustering scheme with the maximum net-

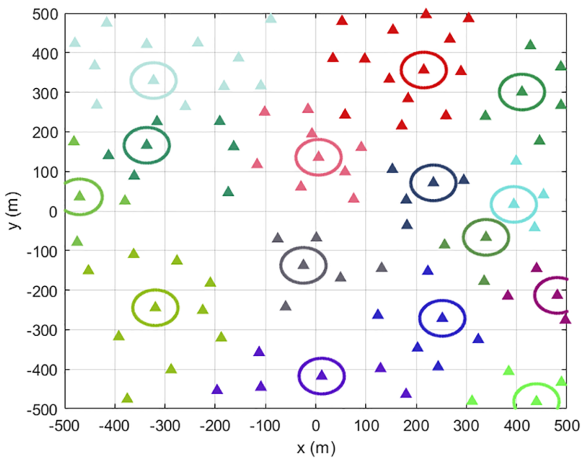

FIGURE 8. Optimal VC clustering scheme (Note: each triangle represents an AP, all triangles with same color belong to same VC, and triangle with circle is selected master AP.).

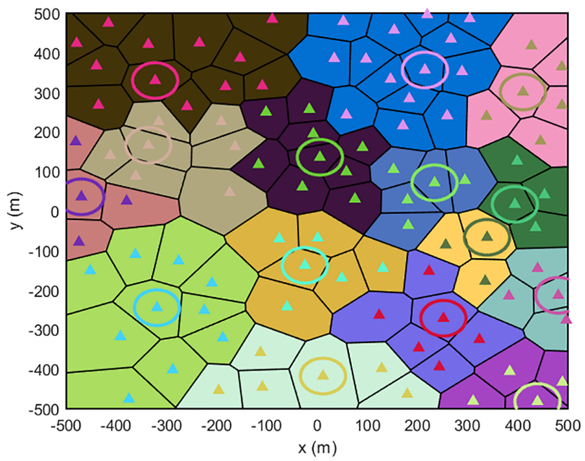

FIGURE 9. Optimal VC boundary scheme (Note: each triangle represents an AP. Coverage of each VC is shown in same color, and triangle with circle is selected master AP.).

work fitness. Compared with Fig. 9, it is obvious that many different colored Voronoi VCs are formed, where the coverage of each VC is shown in the same color. Moreover, Fig. 9 also presents the clustering result with the best network fitness via modified K-means.

VI. CONCLUSION

In this article, a machine-learning-based flexible VC design approach was proposed that jointly considers the backhaul capacity constraint and handoff overhead. We utilized PSO in searching for the optimal VC scheme. The optimal network fitness was quickly attained via a small number of PSO iterations. A modified K-means algorithm as proposed by adopting the weighted distance, enabling cluster APs according to their dynamic traffic demand and backhaul capacity. It was revealed through our simulation analysis that an irregular network topology, dynamic traffic demand on backhaul capacity, and mobility of UEs can be captured by the proposed algorithm in a timely and efficient fashion. Thus, the proposed method is generic to various UDN application scenarios.

In future work, a heterogeneous UDN scenario will be taken into consideration, where other network performance metrics (e.g., handoff delays and VC deployment costs) can be evaluated. In addition, the proposed VC design scheme can be further validated and improved with a test bed or field test.

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