IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received July 2, 2018, accepted August 10, 2018, date of publication August 24, 2018, date of current version September 21, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2867066

FHC-PCIA: A Physical Cell Identification Allocation Method Based on Fuzzy Hierarchical Clustering for Heterogeneous Cellular Network

SHANSHAN TU[1,2], (Member, IEEE), MENG LIU[1], MUHAMMAD WAQAS[3], SADAQAT UR REHMAN[3], RAN ZHU[4], AND LEI LIU[4]

[1]Faculty of Information Technology, Beijing University of Technology, Beijing 100124, China
[2]Beijing Key Laboratory of Trusted Computing, Beijing 100124, China
[3]Department of Electronics and Engineering, Tsinghua University, Beijing 100084, China
[4]Beijing Electro-Mechanical Engineering Institute, Beijing 100074, China

Corresponding author: Meng Liu (timlaumeng@163.com)

This work was supported in part by the Beijing National Natural Science Foundation under Grant L172049, in part by the Beijing Science and Technology Planning Project under Grant Z171100004717001, in part by the National Natural Science Foundation of China under Grant 61671030, and in part by the National Defense Basic Scientific Research Program of China under Grant JCKY2016204A102.

ABSTRACT When users seek for Network in a heterogeneous cellular network, physical cell identification (PCI) is used to distinguish different cellular cells. However, the number of PCIs is extremely limited. Moreover, they are unable to satisfy large-scale random deployment of small cellular cells as well as difficult to guarantee users' quality of service. Therefore, this paper presents a fuzzy hierarchical clustering-physical cell identification allocation scheme. The proposal is based on the ''activity'' of cellular base station (CBS) and uses the Euclidean distance method to obtain the degree of similarities between the CBSs. After dynamic fuzzy clustering, the optimal clustering results are obtained by using the analysis of variance. In this paper, high priority of allocating and reusing the PCIs are given to those CBSs with higher activity. Simulation results show a clear increase in PCI allocation efficiency and reduction in PCI-conflict and PCI-confusion possibilities when compared with the existing schemes.

INDEX TERMS PCI allocation, fuzzy hierarchical clustering, Euclidean distance, heterogeneous cellular networks.

I. INTRODUCTION

Thanks to the continuous development of information technology and the increasing popularity of smart devices, the mobile data traffic has increased by an astonishing 4000 times in the past ten years from 2007 to 2017, and is expected to grow more rapidly up to 30.6 EB/month by 2020 [1]. Similarly, mobile applications have diversified development, such as online video, online games, cloud services, mobile payment and other network applications, that help greatly enriching and facilitating the life of people. Due to the emergence of network applications, numerous network data services are needed. Meanwhile, there is a sharp growth demand for the transmission rate of network services. Therefore, it is urgent to enhance the capacity of cellular cells, especially in the hot areas, such as densely populated areas [2], [3].

In order to solve the problem of the low Quality of Service (QoS) for users, it is proposed to deploy low-power and low-cost small cellular systems on the traditional macro cellular network architectures, this network architecture is called the Heterogeneous Cellular Network (HCN), and the formation of HCN can provide more spectrum resources with larger network capacity [4], [5]. In addition, small cellular cells can be deployed randomly on a large scale in geographical location. However, it is difficult for mobile equipments to identify different cellular cells when searching for network services under the limited PCIs. Consequently, it greatly affects the users' QoS. Observe from Fig. 1, the allocation process can be inordinate and may lead to PCI confusion and conflict [6] between Cellular Base Stations (CBSs) in HCN.

The PCI is challenging as the number of available identifiers is extremely limited. In Long Term Evolution (LTE), there are 168 Physical Layer Cell Identifications(PCIs) and the pool of cell IDs reserved for small cells may be further limited [7]. In addition, using PCIs is desirable for users to search for network service with less network delay.

Consequently, the PCIs need to be efficiently assigned and reused in a way to ensure proper network operation, which means every PCI needs to be clearly identified within an area. Moreover, on account of the reuse of PCIs, PCI assignment conflict and confusion [8] may occur in HCN.

Conflict: It usually occurs when two neighboring CBSs are assigned with the same PCIs. When the users search for network service in the overlapping area, the mobile equipment can at most connect with one small cell. Thus it may connect with the unsuited small cell and the appropriate one is ignored. The schematic is shown in Fig. 1.a.

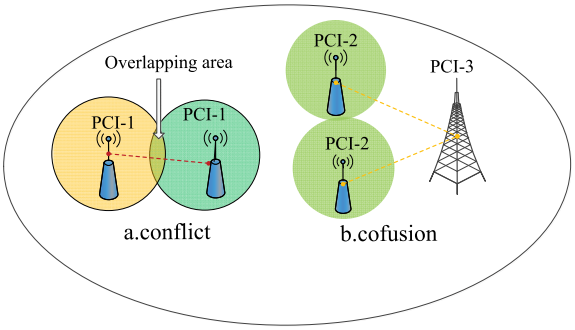

FIGURE 1. PCI confusion and conflict, the colored circular areas represent the coverage of CBSs. Unreasonable PCI allocation and reuse will lead to PCI-confusion and PCI-conflict.

Confusion: In HCN, if two or more neighboring CBSs have the same PCIs, in this case, while the user makes a request to handover the network to another cellular cell allocated with the same PCI, it cannot easily distinguish them, and then may lead to handover failure or wrong handover, as shown in Fig. 1.b.

In the process of calculating the degree of similarities between data objects, Euclidean distance method is an intuitive method. In terms of the Euclidean distance method, the smaller the Euclidean distance is, the greater is the degree of similarity between the two data objects and vise versa. In the HCN, the differences in dimension of CBSs counts to some extend for the ''activity''. Also, it is affected by the magnitude of CBSs. The Euclidean distance method takes into account both the dimension and magnitude of data objects, hence fits the HCN well, and the Euclidean distance between any two data objects shows the degree of similarity. Thus, the proposed FHC-PCIA scheme can be utilized to solve the PCI allocation challenges of numerous cellular cells deployment in HCN.

A. RELATED WORK

In view of the limited PCIs, several schemes have been proposed to solve these problems [9]–[17]. The 3GPP standard protocol [9] uses the Cell Global Identifier (CGI) instead of PCI to assist in identifying and differentiating cellular cells. Although this solution solves the problem of the limited PCIs, yet the communication delay caused by CGI acquisition can seriously affect the users' real-time network service rate and QoS, or even cause network interruption. More importantly, these problems are unacceptable to the users with real-time business. Moreover, the PCIs allocation problem is modeled as a graphic dyeing problem in [10], the proposed method can speed up the allocation and reuse time of PCIs while cannot avoid PCI confusion and conflict. Wu *et al.* [11] propose a two-level clustering approach where cluster head nodes in the first level try to reduce the MAC layer contentions for vehicle-to-vehicle (V2V) communications, and a fuzzy logic-based algorithm is employed in the first-level clustering, this proposed protocol can achieve 23 % improvement in high density scenarios compared to the existing approaches. But this scheme is more appropriate for vehicular networks and lack deep study when applied in HCN. In another article [12], Siavoshi *et al.* proposed a geographical multi-layered energy-efficient clustering scheme for ad hoc distributed wireless sensor networks, although it mitigates the hot spot problem resulting from multi-hop communication with the CBSs, it is difficult to get good QoS for users when the user mobility is random and frequent. The PCIs allocation method is also modeled as a matrix based graphic dyeing algorithm in [13]. The method improves the utilization rate of PCIs but does not consider the users' QoS. Another scheme proposed an improved low-energy adaptive hierarchy protocol for mobile sensor networks in [14]. It uses some user mobility models and reduces the packet loss using fuzzy inference systems but ignores the random and massive deployment of small cellular cells. Mwanje *et al.* proposed an independent layer based on PCI allocation method [15]. A super dense multilayer technique is utilized for the same frequency network in HCN. It reduces the possibilities of PCI conflict and confusion in internal layers. However, this scheme requires relatively long PCI allocation time, and is still unsuitable for real-time business. A centralized PCIs allocation technique is proposed by [16], which is based on TR-069 Management Protocol. This technique reduces the confusion and conflict of PCI allocation. At the meantime, it also introduces overlap in the reference signal mode, which avoids allocating PCIs in adjacent areas, and improves the efficiency of PCIs reuse. In [17], a method of fuzzy hierarchical clustering (FHC) is proposed for the classifications of the CBSs. Here, PCIs are allocated in the CBSs with higher activity. Since, the degree of similarities calculation is based on the Angle Cosine method, and the degree of similarities between CBSs are more reflected by the direction attributes of activity, but ignoring the magnitude of the activity. Therefore, a comprehensive consideration for the parameters' activity of the CBSs is missing.

In view of the above researches deficiencies, we use Euclidean distance method in the clustering of cellular systems. Our method reflects the similarity attributes of the CBSs from the magnitude of the activity. In addition, it is more consistent with the factors associated with the CBS activity.

B. OUR CONTRIBUTIONS

Against the above existing work in this field, our main contributions in this paper is as follows.

- A fuzzy hierarchical PCI allocation model based on activity parameters is proposed in this work. The Euclidean distance method is exploited to solve the fuzzy degree of similarities of different CBSs. In result, it gives us the classifications of the cluster in CBSs under different thresholds.
- The optimal clustering scheme of CBSs is based on Analysis of Variance(ANOVA). This scheme prioritizes the PCIs allocation of CBSs clustering with high activity. It effectively reduces the PCIs allocation time for cellular systems as well as guarantees the users' QoS.
- Simulation experiments illustrated that the proposed scheme is more reasonable in the clustering results of CBSs, improved by over 80% in clustering performance compared the existing schemes.And the proposed method has lower PCI conflict and confusion possibilities in HCN, also the clustering time consumption of our proposed method is improved by 20 % as compared with the PCI allocation scheme proposed in [15].
- The small CBSs in HCN can be deployed randomly with large scales and numbers. In addition, the working state of small CBSs will be changed according to the network environment and the users' requirements. In this paper CBSs are clustered according to the ''activity''. As unknown to the specific numbers of CBSs clusters before dynamic clustering process, therefore, the FHC method is utilized to cluster according to the degree of similarities between diverse CBSs. This scheme can give priority to allocating and reusing PCIs in CBSs with higher activity. Hence, it is not only consider the users' QoS but also the utilization rate of PCIs is improved.

The rest of the paper is organized as follows. In section II, we present preliminaries of our proposed work. Section III describes the system model and its related work. Section IV is devoted to our proposed algorithm, and presents our simulation results in Section V. The paper is concluded in Section VI.

II. PRELIMINARIES

In this section, we explain the preliminaries of FHC, and the general steps involve in the utilization of FHC. First, we illustrate the method of FHC in subsection A. Finally, subsection B involves all the steps in the utilization of FHC, i.e., data normalization, establishing fuzzy similarity matrix (FSM), dynamic fuzzy clustering (DFC), and determination of optimal threshold.

A. FUZZY HIERARCHICAL CLUSTERING (FHC)

Clustering is an unsupervised learning problem, it deals with finding a structure in a collection of unlabeled data. A loose definition of clustering could be the process of organizing objects into groups whose members are similar in some way. A cluster is therefore a collection of objects which are similar between them and are dissimilar to the objects belonging to other clusters. Clustering techniques are classified into two major types: partitional algorithms and hierarchical algorithms [18]. Partitional-clustering algorithms in their outputs produce one clustering set that consists of disjoint clusters, i.e., the data description is flat. However, there are many examples where the input data have the characteristic that its clusters embed subclusters. In such circumstances, clustering methods that lead to representations that are ''hierarchical'' are more appropriate than ''flat'' [19]. Hierarchical-clustering algorithms produce not just one clustering set in their outputs but a hierarchy of clusters.

There is a fact that the activities of CBSs may contain fuzziness, the reason for the fuzziness is that the activities of CBSs might be affected by many factors, such as active users, real-time services, reconnenction services *et al*. Since fuzzy set theory [20] can be used to describe imprecise or fuzzy information, therefore in this paper we use the fuzzy hierarchical clustering method to classify the CBSs in HCN. Another reason that we use the FHC method is that we are unable to get the precise number of clusters before FHC is implemented. Moreover, the FHC method is utilized in order to classify the activities of CBSs and give prioritization with higher activity for allocating PCIs. Generally speaking, items in the same classification tend to have greater degree of similarities while those in different classifications tend to have less [21]. With the advent of the big data era, our lives are full of all kinds of huge data sets. The usage of clustering analysis can effectively reduce the dimension of high dimensional data, and facilitate the analysis and data processing [22].

The hierarchical clustering results are composed of different levels instead of single clustering result, similar to the tree structure. There are several inclusions and nesting relations between hierarchical clustering. The clustering algorithms are often used in the field of social science and computer science engineering [23]. It is a method of fast decomposition and classification of target data sets. According to the method of hierarchical clustering, it is often divided into two ways, namely, merge clustering and split clustering [24], [25]. Merge clustering is a clustering method that merges sequentially from bottom to top. Initially, each datum is classified as a single cluster. The degree of similarity is used to merge data objects and different clusters until all the data objects are clustered into one data cluster or the stopping criteria is satisfied [26]. On other hand, split clustering is a top-to-bottom clustering method. In this method, all the data objects are gathered in one cluster initially, and the previous step of clustering is split into smaller clusters after each step of hierarchical clustering. The process continues until each single data object is aggregated in a certain cluster or the stopping criterion is satisfied [27], [28]. It is not necessary to know the specific number of clusters before fuzzy hierarchical clustering, that is an important feature in FHC. In short, we use clustering method based on fuzzy similarity matrix. This fuzzy similarity matrix is a part of the hierarchical clustering.

B. GENERAL STEPS OF FHC

1) DATA NORMALIZATION

In this portion, first we construction of the data matrix. Let the discourse domain is donated by $U = \{x_1, x_2, x_3, \cdots, x_n\}$, where n contains the objects to be classified and having m indices, to describe its properties, i.e., $X_i = \{x_{i1}, x_{i2}, x_{i3}, \cdots, x_{im}\}$ $(i = 1, 2, 3, \cdots, n)$. The original data matrix is thus obtained as:

$$\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix}$$

a: DATA NORMALIZATION METHOD:

The difference in the data dimension may lead to high variance of data magnitude. Therefore, data normalization is of great necessity. In addition, the effect of the magnitude variance in original data sets can be removed, and data normalization can also make data objects into the same or similar order of magnitude [29]. In practical problems, huge data sets also need to be processed in order to reduce the impact of the magnitude difference on data classification results. In contrast, data normalization processing requires two following transformations steps.

The first step is the shift of standard deviation, and is given as follows.

$$x'_{ik} = \frac{x_{ik} - \bar{x_k}}{S_k} \ (i = 1, 2, \cdots, n; k = 1, 2, \cdots, m), \quad (1)$$

where $\bar{x_k} = \frac{1}{n}\sum_{i=1}^{n} x_{ik}$, and $S_k = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{ik} - \bar{x_k})^2}$.

After standard deviation transformation, the impact of the magnitude of the data attribute values is eliminated from the data results. However, the obtained x'_{ik} can not necessarily satisfy with normalization processing. Therefore, we still need to conduct shift range transform, which is given by:

$$x''_{ik} = \frac{x'_{ik} - \min\limits_{1\le i\le n}\{x'_{ik}\}}{\max\limits_{1\le i\le n}\{x'_{ik}\} - \min\limits_{1\le i\le n}\{x'_{ik}\}} \quad (k = 1, 2, \cdots, m), \quad (2)$$

Each element of the data matrix satisfies $0 \le x''_{ik} \le 1$, after the shift range transformation. This eliminates the difference of magnitude.

2) ESTABLISHING FUZZY SIMILARITY MATRIX (FSM)

In order to carry out fuzzy clustering operation, we need to establish the FSM of data objects after data matrix normalization, i.e., finding the degree of similarities between data objects, denoted as $r_{i,j}$, $\forall i \in n \ \& \ j \in m$. Generally, r_{ij} is called the degree of similarity between data objects, x_i and x_j. There are two common ways to obtain $r_{i,j}$, i.e., the distance method and coefficient of association method.

In order to make it easier and understand the methods to get the degree of similarities, let $d\left(x_i, x_j\right)$, which represents the distance between x_i and x_j. Common methods of distance method and coefficient of association method are Angle Cosine method [17], Manhattan distance method [30], Chebyshev distance method [31], and Euclidean method [32] *et al*. When we use the distance methods such as Euclidean distance method, the degree of similarity with Euclidean distance method [32] is calculated by the following formula:

$$r_{i,j} = 1 - d\left(x_i, x_j\right) = 1 - \sqrt{\sum_{n=1}^{m}\left(x_{in} - x_j\right)^2}. \quad (3)$$

3) DYNAMIC FUZZY CLUSTERING (DFC)

Fuzzy clustering is often used in a dynamic clustering method based on fuzzy equivalence matrix.In the fuzzy mathematics theory [33], the fuzzy similarity relationship is a relationship which is equipped with the reflexivity and symmetry, and the FSM is obtained by using the fuzzy similarity relationship. However, in dynamic fuzzy clustering, we need the to construct a fuzzy similarity equivalence relationship, for this relationship has the reflexivity and symmetry, also necessarily the transitivity. Thus, we need to solve the corresponding transitive closure and make the equivalent partition of the original matrix, i.e., conduct DFC for our original data set. We divide the FSM into proper equivalence by selecting different thresholds after generating the fuzzy equivalent matrix. The selected thresholds start from 1. All data objects are classified into one class when the threshold is equal to 1. The thresholds are going to decrease until it reaches to 0. Hence, we can obtain the clustering results of the original data set under different thresholds. This process is called a dynamic process and is explained in Fig. 2.

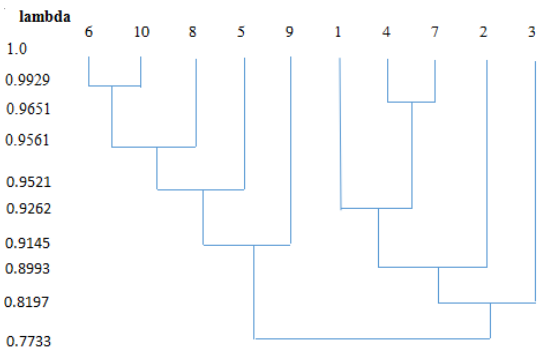

FIGURE 2. DFC process: we made a clustering with ten sample data objects and got the dynamic clustering results under ten different lambda values listed on the left. It can be seen clearly all the data objects are classified into one cluster in the end.

4) DETERMINATION OF THE OPTIMAL THRESHOLD

The ultimate clustering results in fuzzy clustering are different due to the selection of threshold, and the results of hierarchical fuzzy clustering are also different. In practical applications, the selection of the clustering results will have significant impact on the actual results. Consequently, the determination of the optimal threshold is also of great importance.

Therefore, there are two common ways to determine the optimal threshold. One is to find a threshold manually by experts. The manual technique can get the best results in dynamic clustering diagrams according to historical data statistics of actual application, but there are still flaws in empiricism. In HCN, it is difficult to obtain the optimal threshold with historical data for the HCN data has a dynamic change and the amount of CBSs is extremely large. The other way is to use ANOVA in statistics, in which **"F"** statistics is used to obtain the optimal threshold. The larger value of **"F"** provides the better performance in the clustering results. In result, it provides the optimal threshold according to the corresponding threshold. Thus, it generates the optimal results for clustering [34].

III. CELLULAR BASE STATION (CBS) DISTRIBUTION MODEL

The traditional cellular deployment model uses the Wrap-Around model [35], i.e., the coverage of a cellular system in a regular hexagonal with fixed length. This conventional cellular network is also innumerable multiple hexagonal cellular systems, and are embedded into a circular plane with limited size. Thus, it forms the deployment structure of the cellular network. To cover as large an signal area as possible with fewest CBSs deployment, some mathematicians found that only regular hexagons can satisfy this requirement, also the the structure is similar to honeycombs, therefore the network is also called as the honeycomb network. The network is beneficial because it can contribute to a fewest number of CBSs and cost-saving. The topology of the honeycomb network is detailed in Fig. 3.

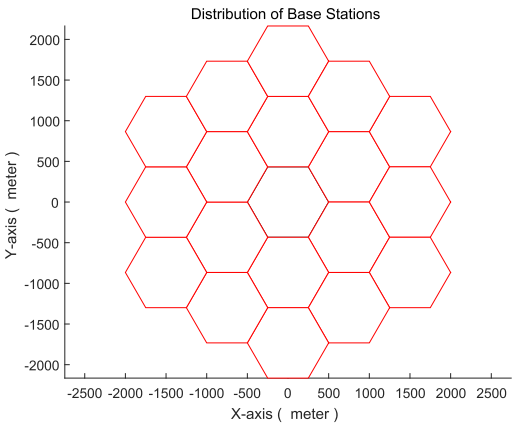

FIGURE 3. A 5000 × 4000 m^2 view of a Wrap-Around model of honeycomb, the red-line regular hexagon grid represents the converge area of a CBS.

With the introduction of the small cellular technology, the quality of the existing network service, and the capacity of the network cell are greatly improved. However, the problem of large number of small cellular systems is due to the emergence of randomness. Subsequently, it is almost impossible to use the traditional Wrap-Around model to simulate the deployment of small CBSs. It is proposed in [36], that the homogeneous Poisson Point Process (PPP) can be used in the random geometry theory to simulate the deployment of the small cellular BS. However, the homogeneous PPP has the following two features, as listed below.

A. FEATURE #1

We choose an Euclidean space region B in space that satisfies the boundaries of the network. Consequently, the number of points in B is subordinate to the Poisson distribution, and the mean is $\lambda \upsilon_d (B)$, where parameter λ represents the distribution expectation of PPP of small CBSs and $\lambda > 0$, $\upsilon_d (B)$ represents the area of B. In other words, for variable $N (B)$ the probability that s points exist in region B is given by

$$P (N (B) = s) = (\lambda \upsilon_d (B))^s \, exp \left(\frac{-\lambda \upsilon_d (B)}{s!} \right). \quad (4)$$

B. FEATURE #2

A series of mutually disjoints and bounded domains $B_1, B_2, \cdots, B_n$ are selected randomly in space regions. The number of points in these regions are independent i.e., $N (B_1), N (B_2), \cdots, N (B_n)$.

The above properties conform to require the actual deployment of small CBSs. We use the PPP model to simulate the deployment of small CBSs. In addition, the common Voronoi model[1] is used for the coverage of small CBSs. The model first assumes some random points in a distributed manner in the space, and the space is divided into several regions, according to the location of each point. The boundaries which make up these areas are the perpendicular bisectors of the adjacent points. Under such planned methods and strategies, each region only belongs to the nearest point. According to investigation, the method of division also conforms to the nearest communication principle in cellular network. Therefore, this small cellular deployment model which is widely used at present [37]. The simulated deployment of small CBSs is shown in Fig. 4.

IV. PROPOSED ALGORITHM

It is considered that users need to search for network service when using the mobile smart devices or encountering network in offline, that involves with the process of physical cell identification. In HCN, the large-scale random deployment of small CBSs requires a large number of PCIs to distinguish each other, while the PCIs is limited, which is insufficient for massive small CBSs deployment. Therefore, in order to make full use of the limited PCIs, we propose a PCI allocation scheme based on dynamic fuzzy hierarchical clustering. Moreover, traditional schemes allocate the PCIs from the overall perspective of CBSs, which resulting in high time complexity. In this paper, by using the proposed algorithm(FHC-PCIA), we reduce the size of CBSs

[1]This model is proposed by mathematician Georgy Voronoi, and widely applied in architecture, physics, and computer network communications.

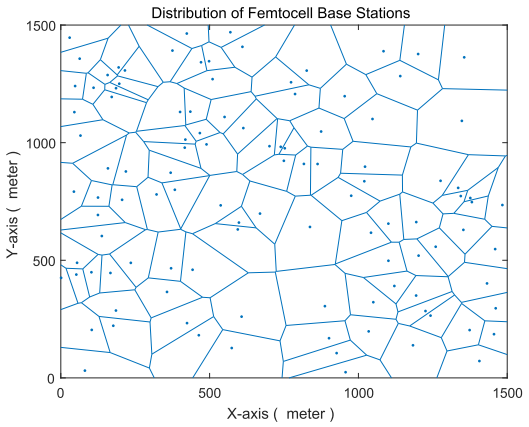

FIGURE 4. A 1500 × 1500 m^2 map of small CBSs, based on PPP model. The cell boundaries are shown and form a Voronoi tessellation. (The distribution expectation $\lambda = 100$).

in allocation process, consequently, effectively saving the allocation time. As in our previous discussion about [17], a dynamic clustering method based on the Angle Cosine method is proposed. Comparatively, we improve the method by adding the step of translation polarization into the process of standardization of the original data. This can transform the data dimension into a more reasonable way. We also adopt the Euclidean distance method to calculate the degree of similarity. It reflects the similar attributes of the CBSs from the data dimension, which is more consistent and has a better clustering performance with the actual situation of the cellular area in HCN. We model the fuzzy clustering scheme as shown in Fig. 5. Observing from Fig. 5, the original cellular distribution map is divided into different clusters, and PCIs allocation and reuse are conducted separately in each of the different clusters.

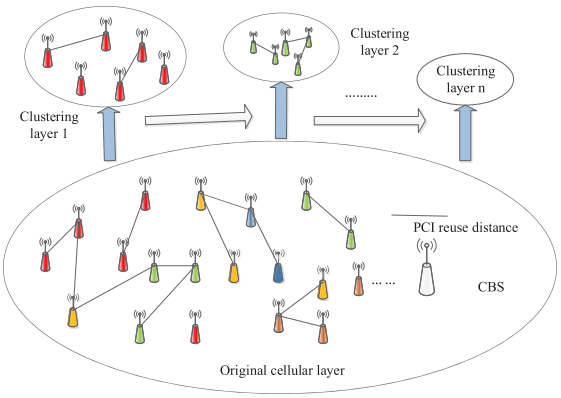

FIGURE 5. FHC of cellular base stations, CBSs with different colors have different degree of similarities, we divide the original cellular layer into *n* clustering layers. The CBSs in the same layer have the same color, and they have higher degree of similarities.

According to the scheme in [17], four factors are set for the active states of a cellular system. The CBSs with higher activity have more online users and real-time services, and then, the CBSs have urgent needs for PCIs allocation to provide network services. Therefore giving priority to these CBSs will effectively guarantee users' QoS. These activity factors include:

1) The real-time switching number of a user in a cellular system P_{ch}.
2) Active user number in a cellular cell P_{us}.
3) Real-time services number of a cellular cell P_{bu}.
4) Session re-connection request number P_{re}.

The statistics of these four types of data in all cellular systems, i.e., $(P_{ch}, P_{us}, P_{bu}, P_{re})$ is made, forming the statistical data matrix BS by

$$BS = \begin{bmatrix} P_{ch}^1 & P_{us}^1 & P_{bu}^1 & P_{re}^1 \\ P_{ch}^2 & P_{us}^2 & P_{bu}^2 & P_{re}^2 \\ P_{ch}^3 & P_{us}^3 & P_{bu}^3 & P_{re}^3 \\ P_{ch}^4 & P_{us}^4 & P_{bu}^4 & P_{re}^4 \end{bmatrix}$$

The following steps are involved in our proposed algorithm.

Step #1 *(Data Normalization):* The normalized data matrix is obtained by using the translation standard deviation transformation and the min-max transformation. If the raw data is not processed, the magnitude difference of the data will have a greater impact on data classification results. Meanwhile, data standardization can avoid numerical problems because large numbers can cause numerical problems. Data normalization can also balance the contribution of the four activity attributes of the CBSs. For example, the clustering method needs to calculate the degree of similarities between data samples. These two transformations are given in (5) and (6).

- Translation standard deviation transformation, i.e.,

$$bs'_{ij} = \frac{bs_{ij} - \bar{bs_j}}{p_j} \quad (i = 1, 2, \cdots, n; j = 1, 2, 3, 4). \tag{5}$$

- Shift and range transformation i.e.,

$$bs''_{ij} = \frac{bs'_{ij} - \min\limits_{1 \le i \le n} \left\{ bs'_{ij} \right\}}{\max\limits_{1 \le i \le n} \left\{ bs'_{ij} \right\} - \min\limits_{1 \le i \le n} \left\{ bs'_{ij} \right\}} \quad (j = 1, 2, 3, 4). \tag{6}$$

Step #2 *(FSM Establishment):* The FSM is given by $s_{i,j} = S\left(bs_i, bs_j\right)$, where S is composed of $s_{i,j}$, and the element $s_{i,j}$ of FSM is calculated by the formula expressed in (7). For any $s_{i,j}$, satisfy $0 \le s_{ij} \le 1$, $s_{ii} = 1$, and $s_{ij} = s_{ji}$. The degree of similarity is higher between bs_i and bs_j, when the value of s_{ij} is closer to 1.

The core content of the Euclidean distance method is to calibrate the direct distance between any two spatial points, which is related to the values of the coordinates of each point. Since, we study the activity degree of CBSs, and the four parameters of activity have almost the equivalent influence factor, we need to calculate the parameters of two CBSs based on absolute distance. Euclidean distance can solve the difference between the actual numerical values of any two data

objects, so it is more widely used to solve the corresponding degree of similarity problem from the numerical values of different dimensions i.e.,

$$s_{ij} = 1 - d\left(bs_i, bs_j\right), \tag{7}$$

where $d\left(bs_i, bs_j\right)$ is denoted as the degree of similarity of bs_i and bs_j, $d\left(bs_i, bs_j\right) = \sqrt{\sum_{k=1}^{4}\left(bs_{ik} - bs_{jk}\right)^2}$ $(1 \le i, j \le n)$.

Step #3 *(Constructing Fuzzy Equivalent Matrix):* We use square method [38] to solve the transitive closure of the FSM S. The detailed steps are as follows.

Starting from FSM S, the squared values are sequentially calculated, $S \to S^2 \to S^4 \to \cdots \to S^{2n} \to \cdots$. When the first time that $S^k \circ S^k = S^k$ holds, it is demonstrated that S^k has transitivity, and S^k is the transitive closure $t\,(S)$.

The definition and operation rules of fuzzy similarity matrix are as follows.

There are three discourse domains U, V, W. Moreover, R_1 is the fuzzy relationship between U and V. The combination result C of R_1 and R_2 is $C = R_1 \circ R_2 = \left(c_{ij}\right)_{m\times n} \in \tau\,(U \times W) = \vee_{k=1}^{s}\left(a_{ik} \wedge b_{kj}\right)$, where $\vee$ and $\wedge$ are Zadeh operators. $\vee$ operator finds the maximum value in a data object set, while $\wedge$ operator finds the minimum. Here, $a_{ik} \wedge b_{kj}$ means getting the maximum value between these two data objects. Then among a series of local maximum values, we use $\vee$ operator to get the global maximum. By this way, the fuzzy equivalent matrix is obtained.

Step #4 *(Dynamic Clustering):* The dynamic clustering is carried out with the transitive closure matrix. We use the square method to find the corresponding transitive closure matrix $t\,(S)$. The required equivalent fuzzy similarity matrix is obtained, which has transitivity, reflexivity and symmetry. By obtaining the equivalent fuzzy similarity matrix, we can take threshold values from 1, and find elements equivalent to 1 in the equivalent fuzzy similarity matrix. If element $p_{i,j} = 1$, it indicates that bs_i and bs_j are in the same cluster, and we cluster the two data objects in one data cluster. It is also considered that different thresholds correspond to different clustering results. The threshold values are certainly selected from the equivalent matrix. The hierarchical clustering method is a bottom-to-top dynamic clustering process. Initially, when the threshold is 1, all data objects are separated individually. As the threshold value decreases from 1 to 0, different clustering results are obtained correspondingly. In result, it develops into a dynamic clustering map of the original data objects, i.e., all the CBSs have been put into different clusters.

Step #5 *(Determination of Optimal Threshold Value* λ*):* The optimal threshold λ should be determined properly, so that the optimal clustering results can be obtained. In actual situations, the optimal threshold can be found and designated to obtain the optimal clustering results, according to the historical experience of experts. Due to high randomness of the small cellular distribution, we cannot accurately predict its activity and clustering results.Therefore, ANOVA in statistics is used in this study, and the **"F"** statistic is used to obtain the optimal threshold. After STEP4, we can obtain the dynamic clustering results under different threshold value, and the **"F"** statistic can be calculated under different threshold value, the threshold value with the biggest **"F"** statistic value is the optimal threshold lambda. In this method, it is not necessary to know the number of clusters in advance according to the application environment of heterogeneous cellular networks. For instance, the number of clusters of all CBSs are denoted by n, the number of CBSs of the j^{th} cluster is n_j, and the samples of the j^{th} are defined as $bs^{(j)} = \left\{x_1^{(j)}, x_2^{(j)}, \cdots, x_{nj}^{(j)}\right\}$. Then, the calculation formula of **"F"** statistics is expressed by (8).

$$F = \frac{\sum_{j=1}^{n} n_j \left\|\bar{x}^{(j)} - \bar{x}\right\|^2 / (n-1)}{\sum_{j=1}^{n}\sum_{i=1}^{n_j}\left\|x_i^{(j)} - \bar{x}^{(j)}\right\|^2 / \left(n_j - n\right)}, \tag{8}$$

where $\bar{x} = \frac{1}{4n}\sum_{i=1}^{n}\sum_{j=1}^{4} bs_{ij}$, $\bar{x}^{(j)} = \frac{1}{n_j}\sum_{k=1}^{n_j} x_k^{(j)}$, $\left\|\bar{x}^{(j)} - \bar{x}\right\| = \sqrt{\sum_{k=1}^{m}\left(\bar{x}_i^{(j)} - \bar{x_k}\right)^2}$ is the degree of similarity between $\bar{x}^{(j)}$ and $\bar{x}$, $\left\|x_i^{(j)} - \bar{x}^{(j)}\right\|$ is the degree of similarity between CBSs activity data $x_i^{(j)}$ and center $\bar{x}^{(j)}$ in the j^{th} cluster.

It is concluded from correlation theorem in statistics that **"F"** statistic is a distribution function satisfying the degree of freedom $\left(n-1, n_j - n\right)$. The denominator is the within group variation, which denotes the variation between data objects in each individual cluster. While its numerator is the variance between different clusters, so it is easy to find out that the larger of the numerator, or the smaller of the denominator, we can get the larger statistic value of **"F"**. In detail, the higher variance between clusters indicates that the data objects in different clusters have lower degree of similarities, which means data objects in different clusters have great differnences. Similarly, smaller variance within clusters indicates the higher degree of similarity between data objects of one cluster, which shows an efficient clustering result. Also, the goal of clustering is to cluster the similar data objects, and the good clustering performance is also benificial for PCIs distribution. Conversely, smaller **"F"** statistic values indicates the clustering result is not satisfactory, and improvement is needed. Therefore, we can calculate the corresponding **"F"** statistic according to the different threshold values. The maximum value **"F"** can be found out and corresponds to the optimal threshold's condition. In result, we obtain the optimal clustering result.

V. EXPERIMENTAL SIMULATION

In this section, we carry out the simulation results in order to test the clustering effect and PCI allocation performance of the proposed scheme. The settings of the simulation parameters are given in Table 1. In the experiments, we use the Angle Cosine method [17], Manhattan distance method [30] and Chebyshev distance method [31] as the benchmark, and the proposed FHC-PCIA for simulation comparison.

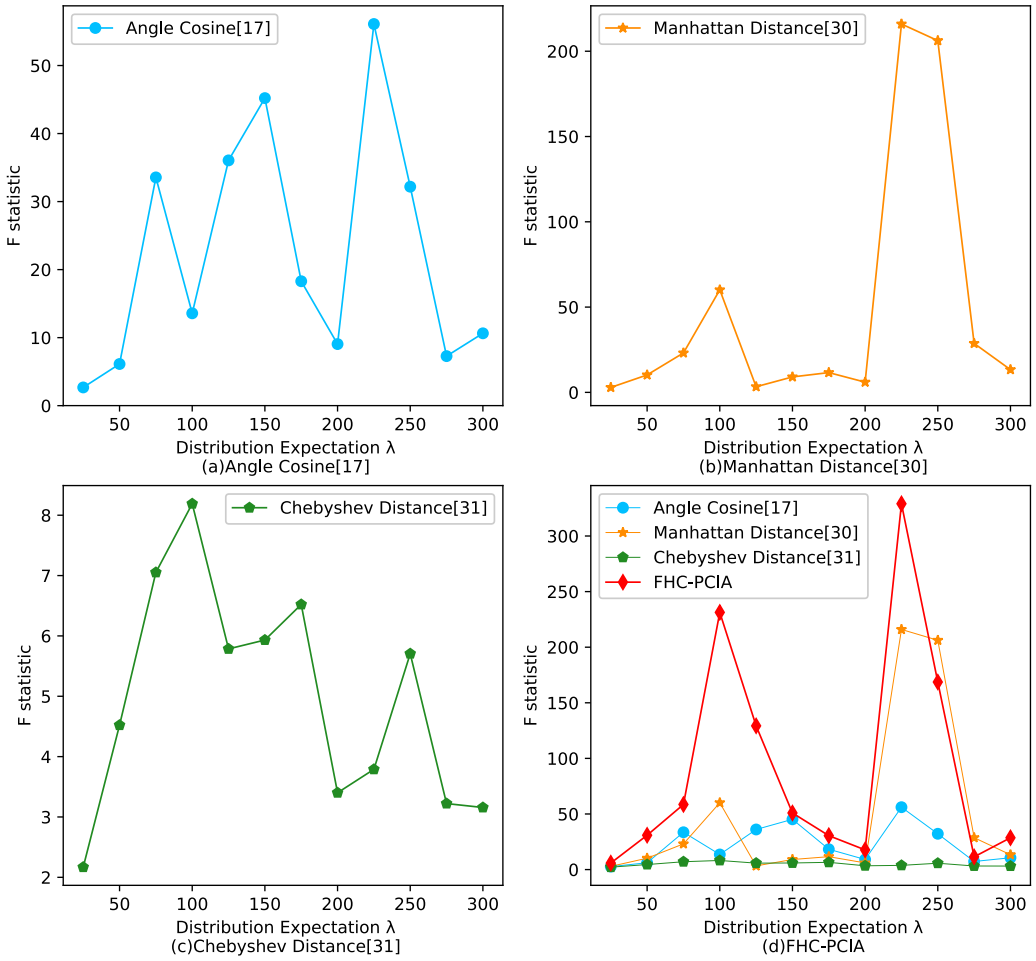

FIGURE 6. **"F" statistic of four schemes. In details, (a) (b) (c) are the single line charts of three methods, (d) is the comprehensive comparison of FHC-PCIA with the other three schemes.**

TABLE 1. **Simulation parameters and environment.**

Parameter name	Parameter value
Macro cellular deployment model	Wrap-Around
Small cellular deployment model	HPPP
Cellular scene size	$1500 \times 1500\ (m^2)$
Simulation tool	JetBrains PyCharm / Windows 10

First, on the basis of the four schemes, the FHC of the CBSs with different distribution expectations is carried out. Then, the **"F"** statistics of each scheme under the corresponding clustering results are calculated. These different line charts of **"F"** statistic are shown in Fig. 6. Secondly, the maximum possibilities of PCI confusion and conflict are calculated by the following formula [39]:

$$P_{cc}^{max} = \frac{\Delta(G) - c + 2}{\Delta(G) + 1} \times 100\%, \tag{9}$$

$\Delta(G)$ denotes the maximum degree of the CBSs neighbor relations graph in a cluster, it usually equals to the number of the CBSs in a cluster minus one, moreover, c is the number of PCIs, which is 168 in the LTE system. Consequently, after the FHC process, we can calculate the maximum possibilities of PCI confusion and conflict and the line chart is shown in Fig.7. Lastly, the clustering time of four schemes are counted and are shown in histogram Fig.8, clearly, lower possibilities of PCI confusion and conflict and clustering time are the key points to the good QoS for users in HCN.

Fig.6 (a) shows the line chart of the changing values using the Angle Cosine method under different distribution expectations of cellular systems. The overall curvilinear form is similar to the sine curve in the trigonometric function with wave peaks and valleys. The **"F"** statistic is decreasing every time after the distribution expectation λ reaches a local optimum, and as λ gets larger, the decline is likely to be sharper. This suggests that the Angle Cosine method might be suitable for some particular distribution density. In summary, the analysis shows that the overall value of the Angle Cosine method is lower in the experiment, indicating that the clustering performance is not ideal.

Fig.6 (b) illustrates the line chart of the changing values using Chebyshev distance method under different

TABLE 2. "F" statistic of four schemes under different distribution expectation λ.

Distribution Expectation λ	25	50	75	100	125	150	175	200	225	250	275	300
Angle Cosine [17]	2.6786	6.1238	33.5551	13.5756	36.0556	45.2112	18.2896	9.0536	56.1029	32.1873	7.2814	10.6352
Manhattan distance[30]	2.8930	10.2307	23.1121	60.1170	3.3101	9.0576	11.5963	5.9946	215.9547	206.2150	28.6914	13.3274
Chebyshev distance [31]	2.1682	4.5213	7.0519	8.1902	5.7848	5.9320	6.5212	3.4011	3.7891	5.7055	3.2220	3.1569
FHC-PCIA	5.8516	30.882	58.5599	231.3124	129.2592	50.8959	30.5128	17.6991	329.0202	168.6798	11.4517	28.6132

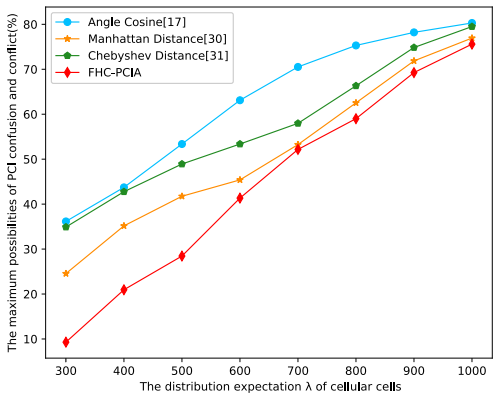

FIGURE 7. The maximum possibilities of PCI confusion and conflict of four schemes under different distribution expectation λ.

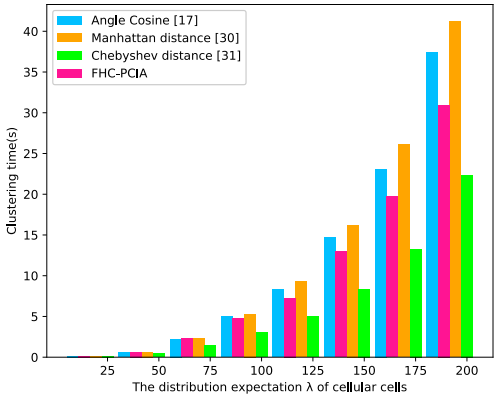

FIGURE 8. The clustering time of four schemes under different distribution expectation λ.

distribution expectation of cellular systems. The changing trend is somehow different from the Angle Cosine method. The main difference is seen when the distribution expectation increases from 100 to 200. The peak values appear in Angle Cosine method, while there is basically no difference in Manhattan distance method and stable trend dominates. The reason is that although the value of every attribute of the CBS activity parameter is different, the Angle Cosine has changed greatly. However, the Manhattan distance does not seem obvious and the results have a steady trend. In general, the values of the Manhattan distance method are relatively large, and the clustering performance is obviously better than the Angle Cosine method.

Fig.6 (c) depicts the line chart of the changing using Chebyshev distance method under different distribution expectation values of cellular systems. The changing trend is basically the same as the previous schemes. The difference is that the total value of Chebyshev method is extremely small, which demonstrates the poor hierarchical clustering performance of this scheme, and is not suitable for the classification of cellular systems. The reason is that Chebyshev distance mainly reflects the biggest difference value of all data dimension attribute values. It is unable to reflect the degree of similarities of CBS activity. Therefore, it is not suitable for the application environment of this study.

Fig. 6 (d) describes the comprehensive comparison of the changing **"F"** statistic using the proposed FHC-PCIA and the other three methods. For FHC-PCIA, the variation trend is similar to the Manhattan distance method. The difference is that the peak value of the Angle Cosine method is larger than the Manhattan distance method when the distribution density increases from 50 to 150. As we can observe from Fig. 6 (d), the proposed method has a notable high **"F"** value despite of the fluctuations. This shows that the proposed scheme is more efficient when applied in the HCN. The reason why FHC-PCIA performs better is that this method is more sensitive to the magnitude of the CBS active states, and not just the dimension of CBS activity. Besides, in the CBSs deployment, the factors that set for the active states of a cellular system count similarly or even equally, and therefore, the magnitude of the factors is of great importance to the clustering results. As for the proposed FHC-PCIA, it has a good reflection on the magnitude difference of CBSs attribute, as we mentioned before, both of the attribute counts in the CBSs active state. So in order to get better clustering results, we should pay more attention on the difference of the attribute magnitude. Clearly, FHC-PCIA satisfies these commands and fits perfectly with the CBSs deployment environment. Above all, the FHC-PCIA is the most efficient method so far.

As shown in Table 2, FHC-PCIA scheme improves the performance by more than 80 % compared with the Angle Cosine scheme in [17] under the condition that the distribution expectation is in accordance with the actual situation. The proposed scheme also outperforms Manhattan distance in [30] when the values are 200 and 300, the reason is that Manhattan distance mainly calculate the total amount of differences in all data dimensions, which often leads to too large degree of similarity and deviates from actual situations.

It is clear from Fig.7 that the maximum possibilities of PCI confusion and conflict using the proposed FHC-PCIA are notably lower than the other three schemes, especially when the distribution expectation is around 300 to 600. This is in line with the actual application when the CBSs are deployed in HCN. On the whole, both of the four curves have a growing trend as the distribution expectation λ gets larger. More specifically, when λ increases from 300 to 700, the curves have a sharp increase on the possibilities of PCI confusion and conflict. From 700 to 1000, the possibilities increase steadily and even reach to 80 % when distribution expectation λ is 1000. In HCN, PCI confusion and conflict may lead to network interruption and handover failure, which greatly affects the QoS for users. Consequently, lower PCI confusion and conflict is the guarantee of good QoS.

Fig.8 is the histogram of clustering time using the four schemes in HCN, it can be seen easily that Chebyshev distance method has the shortest clustering time, for this method mainly concentrates on the biggest differences value of all data dimension attribute values, it does not have to calculate the difference value of all data dimensions. However, Chebyshev distance method have the worst clustering performance in the FHC process and it is not suitable for HCN. As for the proposed FHC-PCIA, the clustering time is less than the Angle Cosine method and Manhattan distance method, which shows that the proposed FHC-PCIA is a faster PCI allocation scheme when applied to HCN. On the whole, when the distribution expectation gets larger, the differences of clustering time get larger between the proposed FHC-PCIA and Manhattan distance and Angle Cosine methods, there is even a 20% reduction of the clustering time when λ is 200. Consequently, the proposed FHC-PCIA could provide better QoS for users in HCN.

To sum up, different methods have been proposed in order to solve the difficulties in the PCIs allocation of CBSs in HCN. However, these methods are not fitted well to the CBSs environment. On the basis of these methods, we proposed the FHC-PCIA to make a better PCI allocation in the CBSs deployment environment. Simulation results prove that the FHC-PCIA scheme has an obvious advantage over other methods, which provides a great driving force for the development of small CBSs.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, a PCI allocation scheme based on FHC is proposed, namely, FHC-PCIA. The degree of similarities of the CBSs is solved by introducing the Euclidean distance method. We conclude that the clustering performance of the cellular systems on the ''activity'' attribute has obvious advantages and can provide better QoS for users in HCN. Finally, through our experimental analysis of the four schemes, we come up with following points.

- We compare our method with the baseline given in [17]. Our proposed FHC-PCIA scheme has a significant improvement in the clustering performance as compared with Angle Cosine method. It is figure out from the simulation results that the proposed FHC-PCIA improves 80 % as compared with the method in [17].
- As for the maximum possibilities of PCI confusion and conflict, FHC-PCIA has obviously lower possibilities than the Angle Cosine, Manhattan distance, Chebyshev distance method, which is the key point of QoS for users.
- More importantly, when comes to the time consuming, the proposed FHC-PCIA has also obvious advantages over other methods, it takes less time and even has a 20 % reduction of the clustering time when λ is 200. Meanwhile it can also ensure the clustering performance.

Based on the above analysis, the distribution expectation become higher when Manhattan distance method holds a slight lead over the FHC-PCIA. Therefore in our future research work, we consider the combination of Euclidean distance method and Manhattan distance method, when the distribution expectation is large to some degree. We could use the Manhattan distance method to achieve better hierarchical clustering performance, and improve the efficiency of PCI allocation in cellular systems.

REFERENCES

[1] G. Feng *et al.*, ''Optimal cooperative wireless communication for mobile user data offloading,'' *IEEE Access*, vol. 6, pp. 16224–16234, 2018.

[2] J. Wen, K. Huang, S. Yang, and V. O. K. Li, ''Cache-enabled heterogeneous cellular networks: Optimal tier-level content placement,'' *IEEE Trans. Wireless Commun.*, vol. 16, no. 9, pp. 5939–5952, Sep. 2017.

[3] A. Asheralieva, T. Q. S. Quek, and D. Niyato, ''An asymmetric evolutionary Bayesian coalition formation game for distributed resource sharing in a multi-cell device-to-device enabled cellular network,'' *IEEE Trans. Wireless Commun.*, vol. 17, no. 6, pp. 3752–3767, Jun. 2018.

[4] X. Ge, S. Tu, G. Mao, and C. X. Wang, ''5g ultra-dense cellular networks,'' *IEEE Trans. Wireless Commun.*, vol. 23, no. 1, pp. 72–79, Feb. 2016.

[5] Y. Qi and H. Wang, ''QoS-aware cell association based on traffic prediction in heterogeneous cellular networks,'' *IET Commun.*, vol. 11, no. 18, pp. 2775–2782, Oct. 2017.

[6] S. S. Mwanje, J. Ali-Tolppa, and H. Sanneck, ''On the limits of PCI auto configuration and reuse in 4G/5G ultra dense networks,'' in *Proc. 11th Int. Conf. Netw. Service Manage. (CNSM)*, Barcelona, Spain, 2015, pp. 92–98.

[7] J. Lim and D. Hong, ''Management of neighbor cell lists and physical cell identifiers in self-organizing heterogeneous networks,'' *J. Commun. Netw.*, vol. 13, no. 4, pp. 367–376, Aug. 2011.

[8] A. P. Lestari, A. N. Mufti, and U. K. Usman, ''Optimization of PCI conflict detection in LTE-advanced using collision and confusion methods considering reuse distance algorithm,'' in *Proc. Int. Conf. Signals Syst. (ICSigSys)*, Bali, Indonesia, 2018, pp. 20–24.

[9] F. Ahmed and O. Tirkkonen, ''Self organized physical cell ID assignment in multi-operator heterogeneous networks,'' in *Proc. IEEE 81st Veh. Technol. Conf. (VTC Spring)*, Glasgow, U.K., May 2015, pp. 1–5.

[10] Y. Wei, W.-B. Wang, M.-G. Peng, and S.-J. Min, ''Graph theory based physical cell identity self-configuration for LTE—A network,'' *J. China Univ. Posts Telecommun.*, vol. 20, no. 1, pp. 101–107, 2013.

[11] C. Wu, T. Yoshinaga, X. Chen, L. Zhang, and Y. Ji, ''Cluster-based content distribution integrating LTE and IEEE 802.11p with fuzzy logic and *Q*-learning,'' *IEEE Comput. Intell. Mag.*, vol. 13, no. 1, pp. 41–50, Feb. 2018.

[12] S. Siavoshi, Y. S. Kavian, M. Tarhani, and H. F. Rashvand, ''Geographical multi-layered energy-efficient clustering scheme for ad hoc distributed wireless sensor networks,'' *IET Wireless Sensor Syst.*, vol. 6, no. 1, pp. 1–9, Feb. 2016.

[13] M. M. Abdulkareem, S. A. Yaseen, and L. M. Abdullah, ''Matrix based graph coloring algorithm for LTE-PCI assignment and reassignment reduction,'' in *Proc. IEEE 8th Control Syst. Graduate Res. Colloq. (ICSGRC)*, Shah Alam, Aug. 2017, pp. 41–46.

[14] J.-S. Lee and C.-L. Teng, ''An enhanced hierarchical clustering approach for mobile sensor networks using fuzzy inference systems,'' *IEEE Internet Things J.*, vol. 4, no. 4, pp. 1095–1103, Aug. 2017.

[15] S. S. Mwanje and J. Ali-Tolppa, "Layer-independent PCI assignment method for ultra-dense multi-layer co-channel mobile networks," in *Proc. IFIP/IEEE Symp. Integr. Netw. Service Manage. (IM)*, Lisbon, Portugal, May 2017, pp. 353–360.
[16] A. Wielgoszewska, D. López-Pérez, H. Claussen, and H. Gacanin, "A centralized method for PCI assignment with common reference signal frequency shift control," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Kuala Lumpur, Malaysia, May 2016, pp. 1–6.
[17] L. Ning, Z. Wang, Q. Guo, and H. Zhang, "Fuzzy layered physical cell identities assignment in heterogeneous and small cell networks," *Electron. Lett.*, vol. 52, no. 10, pp. 879–881, 2016.
[18] Y. Zhao and G. Karypis, "Evaluation of hierarchical clustering algorithms for document datasets," in *Proc. 11th Int. Conf. Inf. Knowl. Manag.*, McLean, VA, USA, 2002, pp. 515–524.
[19] A. K. Jain, M. N. Murty, and P. J. Flynn, "Data clustering: A review," *ACM Comput. Surv.*, vol. 31, no. 3, pp. 264–323, Sep. 1999.
[20] Y.-J. Horng, S.-M. Chen, Y.-C. Chang, and C.-H. Lee, "A new method for fuzzy information retrieval based on fuzzy hierarchical clustering and fuzzy inference techniques," *IEEE Trans. Fuzzy Syst.*, vol. 13, no. 2, pp. 216–228, Apr. 2005.
[21] Z. Cebeci, A. T. Kavlak, and F. Yildiz, "Validation of fuzzy and possibilistic clustering results," in *Proc. Int. Artif. Intell. Data Process. Symp. (IDAP)*, Malatya, Turkey, Sep. 2017, pp. 1–7.
[22] T. Yellamraju and M. Boutin, "Clusterability and clustering of images and other 'real' high-dimensional data," *IEEE Trans. Image Process.*, vol. 27, no. 4, pp. 1927–1938, Apr. 2018.
[23] J. Sangeetha and V. S. J. Prakash, "An efficient inclusive similarity based clustering (ISC) algorithm for big data," in *Proc. World Congr. Comput. Commun. Technol. (WCCCT)*, Tiruchirappalli, India, 2017, pp. 84–88.
[24] S. Gajjar, A. Talati, M. Sarkar, and K. Dasgupta, "FUCP: Fuzzy based unequal clustering protocol for wireless sensor networks," in *Proc. 39th Nat. Syst. Conf. (NSC)*, Noida, India, 2015, pp. 1–6.
[25] A. C. A. Neto, J. Sander, R. J. G. B. Campello, and M. A. Nascimento, "Efficient computation of multiple density-based clustering hierarchies," in *Proc. IEEE Int. Conf. Data Mining (ICDM)*, New Orleans, LA, USA, Nov. 2017, pp. 991–996.
[26] J. W. Jang, M. M. Hossain, and H. J. Lee, "Region-constrained feature matching with hierachical agglomerative clustering," in *Proc. Int. Conf. Comput. Vis. Theory Appl. (VISAPP)*, Lisbon, Portugal, 2014, pp. 15–22.
[27] D. Hofmeyr and N. Pavlidis, "Maximum clusterability divisive clustering," in *Proc. IEEE Symp. Comput. Intell.*, Cape Town, South Africa, Dec. 2015, pp. 780–786.
[28] L. Kaati and A. Ruul, "Interpretable probabilistic divisive clustering of large node-attributed networks," in *Proc. Eur. Intell. Secur. Inform. Conf. (EISIC)*, Athens, Greece, 2017, pp. 68–75.
[29] Y. Qi, B. Luo, X. Wang, and L. Wu, "Load pattern recognition method based on fuzzy clustering and decision tree," in *Proc. IEEE Conf. Energy Internet Energy Syst. Integr. (EI2)*, Beijing, China, 2017, pp. 1–5.
[30] W.-Y. Chiu, G. G. Yen, and T.-K. Juan, "Minimum manhattan distance approach to multiple criteria decision making in multiobjective optimization problems," *IEEE Trans. Evol. Comput.*, vol. 20, no. 6, pp. 972–985, Dec. 2016.
[31] H. Esmaeili-Najafabadi, M. Ataei, and M. F. Sabahi, "Designing sequence with minimum PSL using Chebyshev distance and its application for chaotic MIMO radar waveform design," *IEEE Trans. Signal Process.*, vol. 65, no. 3, pp. 690–704, Feb. 2017.
[32] A. Bonvard, S. Houcke, R. Gautier, and M. Marazin, "Classification based on Euclidean distance distribution for blind identification of error correcting codes in noncooperative contexts," *IEEE Trans. Signal Process.*, vol. 66, no. 10, pp. 2572–2583, May 2018.
[33] H. Bustince *et al.*, "A historical account of types of fuzzy sets and their relationships," *IEEE Trans. Fuzzy Syst.*, vol. 24, no. 1, pp. 179–194, Feb. 2016.
[34] X. Liu, J. Lu, R. Jing, J. Zheng, and J. Li, "Research on F statistic parallel algorithm based on GPU," in *Proc. IEEE Adv. Inf. Manage., Commun., Electron. Automat. Control Conf. (IMCEC)*, Xi'an, China, Oct. 2016, pp. 1469–1472.
[35] H. Elsawy, E. Hossain, and M. Haenggi, "Stochastic geometry for modeling, analysis, and design of multi-tier and cognitive cellular wireless networks: A survey," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 3, pp. 996–1019, 3rd Quart., 2013.
[36] J. G. Andrews, F. Baccelli, and R. K. Ganti, "A tractable approach to coverage and rate in cellular networks," *IEEE Trans. Commun.*, vol. 59, no. 11, pp. 3122–3134, Nov. 2011.
[37] C. Chen and X. Zhao, "Cell boundary user performance in multi-user MIMO Poisson Voronoi cell," *IEEE Commun. Lett.*, vol. 22, no. 4, pp. 772–775, Apr. 2018.
[38] Y. Jiang and G. Deng, "Fuzzy equivalence relation clustering with transitive closure, transitive opening and the optimal transitive approximation," in *Proc. 10th Int. Conf. Fuzzy Syst. Knowl. Discovery (FSKD)*, Shenyang, China, 2013, pp. 461–465.
[39] M. Goonewardena, H. Akbari, W. Ajib, and H. Elbiaze, "On minimum-collisions assignment in heterogeneous self-organizing networks," in *Proc. IEEE Global Commun. Conf.*, Austin, TX, USA, Dec. 2014, pp. 4665–4670.

SHANSHAN TU received the Ph.D. degree from the Computer Science Department, Beijing University of Post and Telecommunication, in 2014. He visited the University of Essex as joint doctoral training from 2013 to 2014. He was with the Department of Electronic Engineering, Tsinghua University, as a Post-Doctoral Researcher, from 2014 to 2016. He is currently an Assistant Professor with the Faculty of Information Technology, Beijing University of Technology, China. His research interests are in the areas of cloud computing, MEC, and information security techniques.

MENG LIU received the B.Sc. degree from South Central University for Nationalities, Hubei, China, in 2017. He is currently pursuing the M.Sc. degree with the Beijing University of Technology. His research interests are in the areas of pattern recognition and machine learning.

MUHAMMAD WAQAS received the B.Sc. and M.Sc. degrees from the Department of Electrical Engineering, University of Engineering and Technology at Peshawar, Peshawar, Pakistan, in 2009 and 2014, respectively. He is currently pursuing the Ph.D. degree with the Beijing National Research Center for Information Science and Technology, Department of Electronics and Engineering, Tsinghua University, Beijing, China. His current research interests are in the areas of networking and communications, including 5G networks, D2D communication resource allocation, and physical layer security and information security, mobility investigation in D2D communication, Fog computing, and MEC.

SADAQAT UR REHMAN received the B.Sc. degree (Hons.) from the Department of Computer Systems Engineering, University of Engineering and Technology at Peshawar, in 2011, and the M.Sc. degree from the Department of Electrical Engineering, Sarhad University of Science and IT, in 2014. He is currently pursuing the Ph.D. degree with the NTN Lab, Department of Electronic Engineering, Tsinghua University, Beijing, China. His current research interests are in the areas of deep learning, including convolution neural networks, unsupervised learning algorithms, and optimization techniques.

RAN ZHU received the B.Sc. degree from the School of Computer Science and Technology, Harbin Institute of Technology, in 2011. She is currently an Engineer with the Beijing Electro-Mechanical Engineering Institute. Her research interests are in the areas of navigation technology, automatic recognition, tracking technology, machine learning, multi-source information fusion, and intelligent decision-making.

LEI LIU received the M.Sc. degree from the School of Aerospace, Mechanical and Mechatronic Engineering, The University of Sydney, Australia, in 2011. He is currently a Senior Engineer and working in the Beijing Electro-Mechanical Engineering Institute. His research interests are in the areas of avionics, mechatronic, robotics, and intelligent systems.