A Data-driven and Load-aware Interference Management Approach for Ultra-Dense Networks

Tao Peng, Member, IEEE, Jiaqi Cao, Xin Liu, Weiguo Dong, Ran Duan, Yannan Yuan, Wenbo Wang, Senior Member, IEEE

Abstract—The ultra-dense network (UDN) has been widely accepted as a promising technology to improve the network performance. However, the severe co-channel interference (CCI) generated due to the densely deployed femtocells greatly limits the network throughput. Different from most conventional methods that model the inter-user interference intensities based on the accurate geographical distance information, which is usually hard to obtain in reality, a more practical machine learning based relative interference intensity modeling method is proposed. The proposed method models the relative interference intensities by mining the resource block (RB) allocation data, the new data indicator (NDI) data, the acknowledgement (ACK) and negative acknowledgement (NACK) data collected from the network, which could achieve an extremely high accuracy that is validated by the simulation results. In addition, we propose a load-aware resource allocation approach which calculates each user’s boundary of reusing the common RBs and allocating the orthogonal RBs with its interfering sources based on the relative interference intensities modeled above and the network load in each transmission time interval (TTI). The orthogonal interfering source set of each user is generated based on its time-varying boundary. Simulation results show that the proposed load-aware resource allocation approach outperforms all the benchmark algorithms under most network densities and network loads especially when the network load is heavy and the network is ultra-dense.

Index Terms—Ultra-dense network, machine learning, association rules, relative interference intensities, acknowledgement and negative acknowledgement

I. INTRODUCTION

The fifth generation (5G) wireless communication networks have higher requirements on the user data rate, the power conservation, the connecting device number and the latency [1]. The ultra-dense network (UDN), where the femtocells are deployed densely, has been widely accepted as a promising technology to meet the requirements of 5G [3].

However, severe co-channel interference (CCI), which puts a serious limitation on the spectral efficiency, will be generated due to the densely deployed femtocells; thus, the interference modeling problem, which is the basic of the interference management problem, is attracting significant attention.

Massive data are always generated in the process of the network operation. Large amounts of useful information, such as the network load and interference information, are implicitly hidden in these data [4]. Such hidden information could be mined by using data mining and machine learning techniques, and could be utilized in adjusting the network configuration and managing the CCI in the network. The machine learning based network data mining provides a novel solution to identify the interference intensities of the network [5]. One motivation of this paper is to utilize the data generated from the network to model the network interference so as to overcome the limitations of the existed work, such as the interference prediction function, etc. In addition, the network load could change quickly because of the emergence of various new mobile services, which could impact the effectiveness of the resource allocation algorithms to a great extent. Therefore, another motivation of this paper is to propose a load-aware resource allocation algorithm which could adjust the resource allocation strategies based on the time-varying network load accordingly and achieve a high spectral efficiency under different network loads.

The main challenge in UDNs is the severe CCI because it puts a serious limitation on the network throughput; thus, the joint scheduling among multiple femtocells to eliminate interference is very important in UDNs. To well support the cooperation and communication between femtocells, the cloud radio access network (C-RAN), whose centralized feature makes it appropriate to support the cooperative techniques, is adopted in this paper. C-RAN evolved from the traditional distributed base stations (BSs) where the processing unit and the radio are integrated together [6]. The C-RAN architecture combines all the computational resources of femtocells into a centralized processor which could be treated as a cloud [7] such as a set of physical servers in a data center, which enables communications among femtocells with low latency and data exchange at high speeds. Such centralized feature could well support the machine learning based interference modeling methods to process a vast number of samples. Therefore, the C-RAN architecture is utilized to model the UDNETWORK in this paper.
A. Related Work

The interference relations are widely recognized and used as the basic of eliminating the network interference so as to improve the network performance [8], [9], [10], [11]. Lots of existing studies have been focused on modeling the interference intensities of networks to help eliminate the severe CCI. Some studies adopted a distance threshold to estimate if severe CCI will be generated between a user equipment (UE) and its interfering femtocell access points (FAPs) [12], [13]. Although geographical distance information could reflect the interference intensities in some ways, the accurate distance information is usually hard to obtain in reality. In addition, geographical distance information cannot determine the propagation characteristics completely so that the distance is not the determinant factor of the network interference. Therefore, it is infeasible to model the network interference only based on the geographical information. The study in [14] employed a signal to interference plus noise ratio (SINR) threshold to measure if UEs and FAPs interfere with each other severely. However, the interference coming from multiple interfering FAPs, whose individual effects cannot be distinguished easily in the actual network, determines the received SINR jointly, which leads to the infeasibility of the received SINR based method. In addition, some conventional methods, such as [15] and [16], relied on the channel states information (CSI) provided by a control channel, which caused large overhead increase [17]. Therefore, it is essential to find a more practical and accurate method to model the network interference.

In addition, most previous studies on solving the resource allocation problem cannot adjust themselves with the variation of the network load which generates a serious impact on the effectiveness of these resource allocation strategies. The work in [18] showed a coloring-based cluster resource allocation method. This method colored the constructed conflict graph first and considered the vertexes (i.e., users) with the same color as a cluster. It allocated spectrum to each cluster based on the ratio of the user number in each cluster to the user number in the whole network. This work ignored the differences of the spectrum requirements of different users, which could lead to an unfair spectrum allocation because a cluster with a larger user number could have a smaller total spectrum requirement. A user-oriented graph based frequency allocation (UGFA) algorithm was proposed in [19], which proposed a two steps graph based frequency allocation mechanism after constructing the interference graph. However, this method is efficient under the condition that only limited nodes deployed in the network. In addition, it is not practical to divide physical clusters in UDN in advance. A real-time opportunistic spectrum access in cloud-assisted cognitive radio networks (ROAR) architecture was proposed in [20], which contained a real-time geo-location database assisted spectrum allocation scheme and an access mechanism. However, it could only serve a single request at a time, which is not efficient enough for UDNs. In [21], a multicell non-cooperative power allocation game framework was presented via pricing. In this algorithm, a water-filling algorithm aiming at maximizing the cell capacity selfishly was utilized to allocate spectrum resource, which could lose the user’s fairness. In [22], a sub-carrier and bit allocation algorithm was proposed. The algorithm reformulated the non-linear optimization resource allocation problem to a linear programming form. However, only the condition of single sub-carrier allocation is considered and the error caused by the reformulation is unknown. The studies above utilized the same strategies under different network loads, which may lead to the insufficient utilization of spectrum resources when the network load is light and lead to the severe CCI when the network load is heavy.

The orthogonal frequency division multiple access (OFDMA) scheme is adopted in this paper, which divided the whole spectrum into multiple resource blocks (RBs). Each RB is composed of several consecutive subcarriers and no spectrum overlap between different RBs. Therefore, when orthogonal RBs\(^2\) are allocated to different UEs, CCI will not be generated; on the contrary, when common RBs\(^3\) are allocated to different UEs, CCI will be generated in the network. The network interference condition in each transmission time interval (TTI) is determined by the resource allocation decisions on each user in the network in the corresponding TTI. The common RBs should be allocated to users who may not generate severe interference to each other such that the spectral efficiency could be improved; vice versa, the orthogonal RBs should be allocated to users who may generate severe interference to each other so as to mitigate severe CCI. However, when the network load is quite heavy, the orthogonal RBs are insufficient even for users who may severely interfere with each other; whereas the orthogonal RBs could also be allocated to users who may not generate severe interference to each other when the network load is light so as to improve the overall throughput. As a consequence, to improve the overall throughput of the network, the resource allocation decisions should be determined by both the network interference condition and the time-varying network load.

B. Main Contributions

To overcome the limitations of the previous studies, we proposed a machine learning based relative interference intensity modeling method and a load-aware resource allocation method in this paper. The former models the relative interference intensities, which could be used in adjusting the resource allocation strategies and eliminating the network interference, in UDNs. Different from conventional methods modeling inter-user interference intensities only based on accurate geographical distance information, the proposed approach is practical and accurate which is validated in Section VI. The latter allocates the spectrum resources based on the modeled relative interference intensities and the time-varying network load. The main contributions of this paper are summarized as follows.

\(^2\)The orthogonal RBs refer to the RBs which are different from each other and have no spectrum overlap with each other.
\(^3\)The common RBs refer to the RBs that occupy the same spectrum resources with each other.
1) A machine learning based relative interference intensity modeling approach: Different from most conventional methods that model the interference intensities based on accurate geographical distance information and the corresponding path loss models (the former is usually hard to obtain in reality and the latter could only represent the transmission loss roughly), a more practical machine learning based relative interference intensity modeling method is proposed. The proposed method models the relative interference intensities by mining the RB allocation data, the new data indicator (NDI) data, the acknowledgement (ACK) and negative acknowledgement (NACK) data. All the data used in this approach could be obtained in the actual network directly, which have been defined in the protocols by the 3rd generation partnership project (3GPP); thus, no additional overhead data transmission burden is added to the network by utilizing the proposed approach. In addition, the proposed method possesses an extremely high accuracy, which is validated by the simulation results, and could be applied to both the down-link and up-link communications.

2) A load-aware resource allocation approach: The proposed load-aware resource allocation approach could adjust the resource allocation strategies based on the time-varying network load. It calculates each UE's boundary of reusing the common RBs and allocating the orthogonal RBs with its interfering sources based on the network load in each TTI. Different from existed cluster based resource allocation methods that separate the network into fixed clusters/groups, the orthogonal interfering source set (i.e., orthogonal interfering FAP set for down-link communications and orthogonal interfering UE set for up-link communications) of each UE is time-varying and calculated based on the corresponding time-varying boundary. Simulation results validate that the proposed approach outperforms than all the benchmark algorithms under most network densities and network loads especially when the network load is heavy and the network is ultra-dense.

C. Paper Organization

The rest of this paper is organized as follows. Section II presents the system model. In Section III, an association rules based relative interference intensity modeling approach is proposed. Section IV presents a load-aware resource allocation scheme. The computational complexities of the proposed methods are analyzed in Section V. Simulation results and analyses are discussed in Section VI. Conclusions are drawn in the following Section VII.

II. SYSTEM MODEL

As shown in Fig. 1, the down-link communications in the ultra-dense scenarios outlined as “Great service in a crowd” focusing on mobile broadband access in very crowded areas and conditions [23], such as stadiums, concerts and shopping malls, are considered in this paper. In these scenarios, the CCI is particularly severe and the interference management is extremely imperative.

A set of FAPs, whose index set is $F = \{1, 2, \ldots, |F|\}$, and a set of UEs denoted by $U = \{1, 2, \ldots, |U|\}$ are densely deployed in a one-floor dual-strip model which consist of a corridor and two strips of subareas on each side of the corridor. Each FAP only serves its subscribed UEs. These FAPs are deployed using a C-RAN architecture as depicted in Fig. 1. Each FAP is connected to the cloud through a fronthaul and the cloud is connected the core network through the backhaul. The centralized feature of C-RAN could well support the cooperative techniques such as interference mitigation in UDNs [6].

UEs accessed to the same FAP do not generate CCI to each other because OFDMA scheme is employed in this paper. The entire system bandwidth is $W$ Hz, which is consist of a set of RBs $R = \{1, 2, \ldots, |R|\}$. Since the deployment of femtocells is ultra dense, the orthogonal RBs could not be allocated to all UEs. Therefore, the conditions of resource reuse are more common in UDNs, which leads to severe CCI.

The received SINR of a UE $i$ served by the FAP $j$ on RB $c$ in the $n^{th}$ down-link TTI, which incorporates the impact of path loss and small-scale fading, could be defined as

$$SINR_{ij,n}^{(c)} = \frac{P_f^{c} \times |G_{ij,n}^{c}|^2}{\sum_{k \in R_{\{j\}}} P_f^{c} \times |G_{ik,n}^{c}|} + \sigma^2$$

where $P_f^{c}$ is the transmission power of FAP $j$ on RB $c$, the total transmission power of FAP $j$ is $P_f = \sum_{c=1}^{|R|} P_f^{c}$, $G_{ij,n}^{c}$ denotes the small-scale fading gain from FAP $j$ to UE $i$ on RB $c$ in the $n^{th}$ down-link TTI, $L_{ij}$ is the path loss from FAP $j$ to UE $i$. The $\sigma^2$ represents the zero mean unit variance of additive white Gaussian noise (AWGN).

III. MACHINE LEARNING BASED RELATIVE INTERFERENCE INTENSITY MODELING

In this section, a machine learning based relative interference intensity modeling approach is presented, which could be applied to both the up-link communications and the down-link communications. It learns the relative interference intensities by mining the data sets collected from the network. Different from traditional methods that model the interference intensities based on specific location information and simplified channel propagation models, the proposed approach models the relative interference intensities without such assumptions since they are hard to obtain in practical networks. The proposed approach achieves a quite high accuracy, which will be validated by simulations in Section V.

In the following subsection A and subsection B, we take the down-link communications as an example to elaborate the proposed relative interference intensity modeling approach.

4The relative interference intensity modeling approach proposed in Section III could be applied to both the up-link and down-link communications. We take the down-link communications as an example to elaborate the proposed approach detailedly and describe briefly how to apply the proposed approach to the up-link communications in the end of Section III.
Fig. 1. System model of the ultra-dense femtocell network
detailedly and describe briefly how to apply this proposed approach to the up-link communications in the end of this section.

A. Data Sets for Learning

Enormous data are generated all the time in practical networks where large amounts of useful information, such as the interference information and the load information, are hidden in these data, which could be used in adjusting the network configurations and resource allocation schemes. Machine learning techniques could be used in mining such hidden information.

In this subsection, we take the down-link communications as an example to explain how to model the relative interference intensities based on the collected data sets.

1) Data Generation: In this paper, the RB allocation data, the NDI data, the ACK and NACK data are used for mining the relative interference intensities. These data are collected from a system-level open source dynamic simulation platform for long-term evolution (LTE) systems which was developed by Polytechnic University of Turin and named LTE-Sim [25]. This platform encompasses several aspects of LTE networks, including both the evolved universal terrestrial radio access (E-UTRAN) and the evolved packet system (EPS) [25]. In particular, it supports the single- or multi-cell environments, the quality of service (QoS) management, the multi-user environment, the user mobility, the handover procedures, the frequency reuse techniques, the various scheduling strategies, the adaptive modulation and coding (AMC) scheme, and the channel quality indicator (CQI) feedbacks [25]. To make the data generated from the simulation platform more accurate compared with those from real networks, the up-link transmission power control (TPC) module, the diversity module and the hybrid automatic repeat request (HARQ) module have been added by us to the LTE-Sim platform.

Users could be deployed with the voice over internet protocol (VoIP) services and the Video services in the LTE-Sim platform, where the packet size and the packet interval of each VoIP service are 32 bytes and 20 TTIs, the packet size of each Video service is a random number between 40 bytes and 10000 bytes, the packet interval of each Video service is a random number between 20 TTIs and 60 TTIs. Each service has a random start time and a configured duration to control the generation of data packets. After the parameters of each service are configured, the users who have spectrum resource requests in the corresponding TTI are scheduled by the user scheduling algorithm (such as round robin, proportional fairness, etc.) adopted by the LTE-Sim platform; therefore, different sets of users are scheduled in different TTIs.

Fig. 2 shows the data generation process. In the LTE system, the down-link reference signals transmitted by UE i’s associated FAP j in the nth down-link TTI are used to measure the SINR at each RB of UE i [26] in the corresponding TTI. Then the measured SINR data at the RBs which are occupied by UE i in the nth down-link TTI are used to calculate the effective SINR of the corresponding TTI. Since different RBs go through different fading characteristics, the

6NDI, whose length is 1 bit, is used for presenting new transmission or re-transmission by judging if it has been toggled comparing to the previous received transmission value [24]. In addition, the NDI data are transmitted in the down-link control information (DCI), which has been defined in the protocol by 3GPP.

7Given space limitations, no more detailed introduction of the LTE-Sim platform will be made, please refer to reference [25].
In this paper, the CQI feedback is calculated according to the effective SINR value of the past $T$ TTIs (i.e., the $(n - T + 1)^{th}$ TTI, the $(n - T + 2)^{th}$ TTI, ... , the $n^{th}$ TTI). In addition, the CQI feedback of each RB each TTI should be reported. Since feeding back CQI at each RB could be considered as a special case of subband CQI feedback scheme when each subband only contains one single RB, the presented method is suitable for nonperiodic subband CQI feedback scheme defined in [28] as well. Rather than analyzing the common allocated RBs, the common allocated subbands should be analyzed when the subband CQI feedback scheme is considered [4]. In addition, the nonperiodic CQI feedbacks could be considered as a subset of the periodic CQI feedbacks.

**ASSOCIATION RULES BASED RELATIVE INTERFERENCE INTENSITY MODELING**

In this subsection, the reasons why the association rules algorithm is chosen to mine the relative interference intensities based on the selected data are given first. Then the detailed steps of the association rules based relative interference intensity modeling algorithm are stated.
1) Reasons of Choosing the Association Rules Algorithm:
As stated in subsection A.1) of Section III, the feedback of ACK or NACK represents whether the corresponding transmission is successful or not, which is related to the interference conditions both in the current down-link TTI (i.e., the \((n+1)\)th down-link TTI) and in the past \(T\) down-link TTIs (i.e., the \((n-T+1)\)th down-link TTI, the \((n-T+2)\)th down-link TTI, ..., the \(n\)th down-link TTI). The ACK or NACK feedback of the \((n+1)\)th down-link TTI is determined by the interference conditions and the MCS of the current TTI. The latter indicates the interference intensities of the past TTIs because the MCS of the \((n+1)\)th down-link TTI is obtained based on the CQI feedback of the \(n\)th down-link TTI which is derived from the effective SINR of the past \(T\) down-link TTIs. In this situation, the change of the MCS values in adjacent TTIs could be small. In addition, the larger the \(T\) is, the smaller the change of the MCS values in adjacent TTIs is. Therefore, the feedback of ACK or NACK of the \((n+1)\)th down-link TTI is mainly affected by the interference conditions of the current TTI, which is determined by the RB allocation decisions of the current TTI. The larger the total interference intensity received from the interfering FAPs is, the larger the possibility of failing to demodulate the received data packet will be (i.e., sending an NACK feedback), and vice versa.

We draw an important conclusion above which has a significant influence on the selection of the machine learning method. Each received ACK or NACK feedback is determined by multiple interfering sources jointly. To analyze the interference intensity coming from a certain interfering FAP \(k\) on UE \(i\), a vast number of samples which contain the situations that FAP \(k\) generated interference to UE \(i\) are needed to calculate the corresponding possibilities stated above. Since the calculation of the corresponding possibilities has the same principles with the confidence calculation\(^9\) in the association rules algorithm, we choose the association rules algorithm to mine the relative interference intensities in this paper.

2) Relative Interference intensity modeling: In the conventional association rule analyses, the association rules of items are learnt by calculating the support value and the confidence value. The support value reflects the probability of the item

\(^9\)The association rules algorithm is a rule-based machine learning method for discovering relations between variables (i.e., support calculation) and how strong the discovered relations are (i.e., confidence calculation) in large databases. The confidence is an indication of how often the rule or relation has found to be true.
set \( \{X, Y\} \) existing in the whole data set [29], which is used for finding the frequent item sets [4]. The confidence value represents the probability of including \( X \) in the sample set including \( Y \) [29]. In this paper, each interfering FAP of a certain UE \( i \), corresponding to an item of UE \( i \)'s data set (i.e., \( D'_i \)), will generate interference to UE \( i \) if they are allocated with the same RBs. Therefore, the support calculation is unnecessary in this paper because each UE and each of its interfering FAPs could be considered as a frequent item set. Moreover, the relative interference intensities of the interfering FAPs of a certain UE \( i \) is determined by the confidence values. The larger the confidence value of the item set consisting of UE \( i \) and its interfering FAP \( k \) is, the stronger the interference received by UE \( i \) coming from FAP \( k \) will be.

The proposed association rules based relative interference intensity modeling algorithm is stated below and summarized in Algorithm 1.

**STEP 1:** Preprocess the collected data as stated in subsection A. 2) of Section III.

**STEP 2:** For each interfering FAP of UE \( i \), calculate the confidence value of item set \( \{i, k\} \) \((i \rightarrow j, k \in F_j)\) based on the data set \( D'_i \). The confidence value of item set \( \{i, k\} \) is calculated as follow

\[
c(i, k) = \frac{a_{i,j,NACK}^{k,NACK}}{a_{i,j,ACK}^k}(s' \in D'_i)
\]

where \( a_{i,j,NACK}^{k,NACK} \) represents the value corresponding to a NACK sample and the interfering FAP \( k \) in UE \( i \)'s data set \( D'_i \).

**STEP 3:** Arrange the confidence values of UE \( i \) and its interfering FAPs \((i.e., c\{i, k\}(i \rightarrow j, k \in F_j))\) in ascending order. Take the order number of each interfering FAP of UE \( i \) (i.e., \( o\{i, k\} \)) \((i \rightarrow j, k \in F_j)\) as the relative interference intensity\(^{10}\); thus, the relative interference intensity from FAP \( k \) to UE \( i \) is \( I_{i,k} = o\{i, k\} \in \{1, 2, \ldots, |F| - 1\} \). The larger the confidence value \( c\{i, k\} \) is, the larger the order number is, the stronger the interference generated from FAP \( j \) to UE \( i \) will be.

**STEP 4:** Repeat **STEP 2** to **STEP 3** until the relative interference intensities of all users have been analyzed.

It is reasonable to use the order numbers to represent the relative interference intensities. The larger the order number is, the larger the confidence value is, the severer the interference is. In addition, the load-aware resource allocation algorithm proposed in this paper only utilizes the relative interference relations rather than using the orders as the real interference values directly. Therefore, we sort the confidence values in ascending order and use the order numbers as the relative interference intensities in this paper.

\(^{10}\)The value of the relative interference intensity (i.e., the order number) doesn’t represent the real interference value. The relative interference intensities modeled in this paper only indicate that the interference coming from which interfering source is severer among all interfering sources of a certain UE. For example, UE \( i \) has two interfering FAPs \( k_1 \) and \( k_2 \) whose relative interference intensities are 1 and 2, respectively. In this situation, the interference coming from \( k_2 \) is severer than that coming from \( k_1 \), but it doesn’t mean the interference coming from \( k_2 \) is twice as strong as the interference coming from \( k_1 \).

<table>
<thead>
<tr>
<th>Algorithm 1</th>
<th>Association rules based relative interference intensity modeling</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1:</strong> Part 1: Data Preprocessing</td>
<td></td>
</tr>
<tr>
<td><strong>2:</strong> Part 2: Model relative interference intensities based on the association rules algorithm</td>
<td></td>
</tr>
<tr>
<td><strong>3:</strong> for ( i \in U ) do</td>
<td></td>
</tr>
<tr>
<td><strong>4:</strong> for ( k \in F_j(i \rightarrow j) ) do</td>
<td></td>
</tr>
<tr>
<td><strong>5:</strong> Calculate the confidence value of the item set ( {i, k} ) as ( c{i, k} = \frac{a_{i,j,NACK}^{k,NACK}}{a_{i,j,ACK}^k}(s' \in D'_i) )</td>
<td></td>
</tr>
<tr>
<td><strong>6:</strong> end for</td>
<td></td>
</tr>
<tr>
<td><strong>7:</strong> Arrange ( c{i, k} ) in ascending order and get the order numbers ( o{i, k} ) (\in {1, 2, \ldots ,</td>
<td>F</td>
</tr>
<tr>
<td><strong>8:</strong> end for</td>
<td></td>
</tr>
<tr>
<td><strong>9:</strong> Output: Output the relative interference intensities ( o{i, k}, \forall i \in U, i \rightarrow j, k \in F \cap \forall j )</td>
<td></td>
</tr>
</tbody>
</table>

The numbers of the common allocated RBs between a certain UE \( i \) and each of its interfering FAPs are different from each other. The multiple common allocated RBs between UE \( i \) and its interfering FAP \( k \) affect the ACK or NACK feedback sending from UE \( i \) to FAP \( k \) jointly. The larger the number of the common allocated RBs between UE \( i \) and its interfering FAP \( k \) is, the larger the influence coming from FAP \( k \) on the ACK or NACK feedback of UE \( i \). Therefore, we improve the confidence calculation formula as shown in equation (2), which considers the influence of the number of the common allocated RBs corresponding to both the ACK and NACK feedback.

There are some advantages of utilizing the association rules algorithm to mine the interference relations of the network. First, the association rules algorithm could separate the influences (i.e., interference) coming from different interfering sources, which is really hard to realize by utilizing traditional methods, such as interference sensing in the wireless sensor network. Second, the association rules algorithm could obtain the relative interference intensities based on the calculated confidence values. That is to say, the influence of which interfering FAP on a certain UE \( i \) is stronger among all interfering sources of UE \( i \) could be obtained, which is hard to achieve by other machine learning methods, such as, the decision tree.

### C. Application for Up-link Communications

To apply the relative interference intensity modeling approach proposed above to up-link communications, the RB allocation data, the NDI data, the ACK and NACK data in up-link TTIs should be collected. In addition, the relative interference intensities between each UE and its interfering UEs instead of the relative interference intensities between each UE and its interfering FAPs should be analyzed in the up-link interference analyses. In other words, the common allocated RBs between each UE and its interfering UEs should be calculated in the data preprocessing processes and the confidence value of item set \( \{i, l\}(i \rightarrow j, l \rightarrow k, i, l \in \)
U, j ∈ F, k ∈ F(j) should be calculated. Besides the differences stated above, the rest processes of the up-link relative interference analyses are the same with the down-link relative interference analyses elaborated in subsection A and subsection B of this section.

IV. LOAD-AWARE RESOURCE ALLOCATION

As stated in Section I, when the network load is quite heavy, the orthogonal RBs are insufficient even for users who may severely interfere with each other; whereas orthogonal RBs could also be allocated to users who may not generate severe interference to each other when the network load is light so as to improve the overall throughput. As a consequence, to improve the overall throughput of the network, the resource allocation decisions should be determined by both the interference conditions and the time-varying network load.

In this section, a load-aware resource allocation algorithm, which is implemented based on the relative interference intensities obtained in Section III and the network load of each TTI, is proposed.

Definition 1 (Network Load): The network load is the ratio of the average RB number needed by all UEs accessed to each FAP to the total RB number of the network. The network load of the nth up-link/down-link TTI is defined as

\[ Load(n) = \frac{\left\lceil \frac{\sum_{i=1}^{U} N_{i,n}}{|F|} \right\rceil}{|R|} \]  

where \( N_{i,n} \) is the RB number that needs to be allocated to UE i in the nth up-link/down-link TTI, which is the ratio of the packet size to be transmitted by/to UE i in the nth up-link/down-link TTI to the average data rate of all users accessed to UE i’s associated FAP j (i.e., \( i \rightarrow j \)) at all RBs in the last up-link/down-link TTI (i.e., the \((n-1)^{th}\) up-link/down-link TTI). \( N_{i,n} \) is mathematically defined as follows.

\[ N_{i,n} = \frac{\sum_{l \rightarrow j} \sum_{k=1}^{|R|} \phi_{i,n}}{\sum_{l \rightarrow j} \sum_{k=1}^{|R|} R_{i,n-1}^{(k)}} \]  

where \( \phi_{i,n} \) is the packet size to be transmitted by/to UE i in the nth up-link/down-link TTI. \( R_{i,n-1}^{(k)} \) is the data rate achieved by user l(\( \rightarrow j \)) at RB k in the \((n-1)^{th}\) up-link/down-link TTI and calculated by \( R_{i,n}^{(k)} = \log_{2}(1+SINR_{i,n}) \). |R| represents the total RB number in the network.

A. The Boundary of Allocating Common or Orthogonal RBs

The proposed approach calculates each UE’s boundary of reusing the common RBs and allocating the orthogonal RBs with its interfering sources (hereinafter referred to as the boundary) based on the network load in each TTI. The boundary of UE i in the nth up-link/down-link TTI is the maximal range that orthogonal RBs could be allocated to both UE i and its interfering sources (i.e., interfering FAPs for down-link communications and interfering UEs for up-link communications) within the boundary, which are severe interfering sources of UE i, under the condition that all interfering sources within the boundary occupy orthogonal RBs with each other. UE i could occupy the common RBs with interfering sources beyond the boundary. Assuming that UE i is allocated with several RBs \( C_{i} = \{c_{1}, c_{2}, ..., c_{|C_{i}|}\} \), its common RBs is the RBs belonging to \( C_{i} \) and its orthogonal RBs is other RBs except the RBs in \( C_{i} \).

The number of RBs needed by each UE in each TTI is time-varying; thus, the boundary of each UE is time-varying as well. The boundary of UE i in the nth up-link/down-link TTI, which could be calculated based on the number of RBs needed by each UE in the corresponding TTI, is mathematically described in (5a)/(5b).

\[ B_{up}(i,n) = \max_{B}(|N_{j,n} + \sum_{q=1}^{B} N_{q,n} | \leq |R|), \]  

\( i \rightarrow j, q \rightarrow k, k \in F \setminus B, B \leq |U| - |U_{F,i}| \)

\[ B_{down}(i,n) = \max_{B}(|N_{j,n} + \sum_{p=1}^{B} N_{p,n} | \leq |R|), \]  

\( i \rightarrow j, p \in F \setminus j, B \leq |F| - 1 \)

where \( N_{j,n} \) is the RB number requested by UE i’s associated FAP j in the nth up-link/down-link TTI (i.e., the total RB number needed by all UEs accessed to FAP j in the nth up-link/down-link TTI, which could be calculated as \( N_{j,n} = \sum_{i \rightarrow j} N_{i,n} \)). \( N_{p,n} \) is the RB number needed by the pth strongest interfering FAP of UE i. \( N_{q,n} \) is the RB number needed by the qth strongest interfering UE of UE i. |U_{F,i}| represents the user number accessed to UE i’s associated FAP j. |R| represents the total RB number in the network. \( B_{up}(i,n)/B_{down}(i,n) \) represents the number of UE i’s interfering UEs/FAPs within the boundary. It finds the biggest range for each UE where the orthogonal RBs could be allocated to UE i and its most severe interfering sources within the range under the condition that all interfering sources within the boundary are allocated orthogonal RBs with each other.

Fig. 4 is an example of the boundaries of the same down-link network under different network loads. Fig. 4 (a) and Fig. 4 (b) show UE 1’s boundaries of reusing the common RBs and allocating the orthogonal RBs with its interfering FAPs, which is calculated according to equation (5b), under the heavy and the light network loads, respectively. There are 9 UEs in the network and each UE is accessed to an FAP. The RB requirement of each down-link is given in Fig. 4. There are 20 orthogonal RBs in the network. It could be known that the total RB requirement of the network is larger than 20; thus, orthogonal RBs cannot be allocated to each UE.

When we consider to allocate RBs to UE 1, the orthogonal RBs should be allocated to both UE 1 and its several most severe interfering FAPs to avoid severe interference. Since there are only 20 RBs in the network, the total RB requirement of UEs within the boundary of UE 1 should not exceed 20. It worth to notice that the boundary isn’t calculated based on distance information but the relative interference intensities modeled in this paper. It could be known from Fig. 4 that when the network load is heavy, there could be less UEs/FAPs within the boundary (Fig. 4 (a)) and vice versa (Fig. 4 (b)).

Therefore, it could be known that the boundary of UE i
Fig. 4. The boundaries of the down-link communication network under different network loads

in the $n^{th}$ up-link/down-link TTI is the maximal range that orthogonal RBs could be allocated to both UE $i$ and its interfering UEs/FAPs within the boundary (i.e., the severe interfering FAPs) even under the condition that all interfering sources within the boundary are allocated with orthogonal RBs with each other. UE $i$ could occupy the common RBs with interfering sources beyond the boundary.

**B. The Load-aware RB Allocation Algorithm**

The boundary of UE $i$ in the $n^{th}$ up-link/down-link TTI separates its interfering sources into two subsets. One subset includes the interfering sources that occupy the orthogonal RBs with UE $i$. The other subset includes the interfering sources that occupy the common RBs with UE $i$. Each UE has an individual boundary which is time-varying and related to the network load. By calculating the boundary of each UE in each TTI, we could obtain the maximal range stated in subsection A of Section IV of each UE. These maximal ranges might partially overlap with each other. UE $i$ could occupy the common RBs with interfering sources beyond the boundary.

**STEP 1:** Calculate the boundary of each UE in the $n^{th}$ down-link TTI based on (5b).

**STEP 2:** Generate the orthogonal interfering FAP set of each UE based on the boundaries obtained in **STEP 1**. The orthogonal interfering FAP set $O_{i,n}$ of UE $i$ in the $n^{th}$ down-link TTI could be calculated as follow:

$$O_{i,n}^1 = \{ k \mid I_{i,k} \leq B_{\text{down}}(i,n) \}$$

$$O_{i,n}^2 = \{ k \mid I_{v,k} \leq B_{\text{down}}(v,n) \land I_{v,j} \leq B_{\text{down}}(v,n) \}$$

where equation (6a) indicates that the interfering FAPs within the boundary of UE $i$ corresponding to the $n^{th}$ down-link TTI are added into $O_{i,n}^1$. Equation (6b) indicates that FAP $k$ needs to be added into $O_{i,n}^2$ when the FAP $k$ and UE $i$’s associated FAP $j$ are both within the boundary of another UE $v$. 

**Definition 2 (Idle RB):** The idle RBs of UE $i$ in the $n^{th}$ up-link/down-link TTI are the RBs that have not been allocated to UE $i$ and the UEs accessed to the FAPs belonging to $O_{i,n}$.

**STEP 3:** Allocate an idle RB to UE $i$ if it is available; otherwise, reuse the common RB with the interfering FAP which has the weakest relative interference intensity among all interfering FAPs that belong to $O_{i,n}$.

**STEP 4:** Repeat **STEP 3** until the RB requirements of UE $i$ (i.e., $N_{i,n}$) have been satisfied.

**STEP 5:** Repeat **STEP 3** to **STEP 4** until the RB requirements of all UEs have been satisfied. 

The **STEP 3** of Algorithm 2 indicates that if there is no idle RB available for UE $i$, we should reuse the RBs that have been allocated by the interfering FAP which has the weakest relative interference intensity.
Algorithm 2 A load-aware RB allocation algorithm

1: for TTI $n$ do
2:   for $i \in U$ do
3:     Calculate $B_{down}(i, n)$ based on (5b)
4:   end for
5: for $i \in U$ do
6:   Generate $O_{i,n}$ based on (6a), (6b) and (6c)
7: end for
8: for $i \in U$ do
9:   Set $\text{temp} = 0$
10:   while $\text{temp} < N_{i,n}$ do
11:     if Idle RBs available for UE $i$ then
12:       Allocate UE $i$ with an idle RB
13:     else
14:       Find FAP $k = \arg\min(I_{i,k})$ ($k \in O_{i,n}$)
15:       Allocate UE $i$ with an RB which has been allocated to FAP $k$
16:     end if
17:     $\text{temp} = \text{temp} + 1$
18:   end while
19: end for
20: Output: Output the RB allocation results of all users.
21: end for

interference among all strong interference FAPs belonging to $O_{i,t}$, to its associated UEs.

V. COMPUTATIONAL COMPLEXITY ANALYSES

Assuming that there are $\alpha$ UEs and $\beta$ FAPs ($\alpha \geq \beta$) in the network. In addition, the number of samples in the dataset $D_i'$ is $K$ ($\alpha, \beta << K$).

First, we analyze the computational complexity of Algorithm 1. To generate the dataset $D_i'$ of each UE, the number of the common allocated RBs between UE $i$ and each of its $\beta - 1$ interfering FAPs of each sample in $D_i'$ should be calculated. Therefore, the computational complexity of the preprocessing process of all UEs (i.e., the STEP 1 of Algorithm 1) is $O(K \times (\beta - 1) \times \alpha) \sim O(\alpha \beta K)$. The computational complexity of the confidence value calculation (i.e., the STEP 2 of Algorithm 1) is $O(K \times (\beta - 1)) \sim O(\beta K)$. The third step of Algorithm 1 is a sorting algorithm and its complexity depends on the specific selected sorting algorithm. We take bubble sorting algorithm as an example, the computational complexity of STEP 3 is $O(\beta^2)$. Both the STEP 2 and STEP 3 need to be repeated for $\alpha$ times; thus, the total computational complexity of Algorithm 1 is $O(\alpha \beta K + (\beta K + \beta^2) \times \alpha) \sim O(\alpha \beta K + \alpha \beta^2)$. Since $\alpha, \beta << K$, the computational complexity of Algorithm 1 could be considered as $O(\alpha \beta K)$ approximately.

Except STEP 1 (i.e., Algorithm 1), the computational complexity of the rest steps of Algorithm 2 is $O(A \times \alpha) \sim O(\alpha)$ ($A$ is a finite natural number) because the RB allocation decision of each UE is accomplished by finite basic calculations, which could be ignored comparing with the computational complexity of STEP 1 (i.e., $O(\alpha \beta K)$).

As a consequent, the overall computational complexity of the proposed data-driven and load-aware interference management approach is $O(\alpha \beta K)$.

VI. SIMULATION RESULTS AND ANALYSES

A one-floor dual-strip model shown in Fig. 1 is adopted in this paper. The width of each square subarea and the corridor are both 10 meters. A set of femtocells are densely deployed in this model, which could be considered as UDN. Only one FAP is placed in each subarea and only one UE is accessed to each FAP. Both UEs and FAPs are deployed randomly in the corresponding subareas. The system Bandwidth $W$ is 10 MHz which consists of 50 RBs. The transmission power $P_f$ of each FAP is 20 dBm and the density of AWGN is -174 dBm/Hz. In addition, the indoor path loss model $(38.46 + 20 \log_{10}(d))$ dB in $[30]$ is adopted in this paper.

In this paper, three VoIP services and one Video service are configured to each user. The total data generation duration is 2500 seconds, which corresponding to 100000 down-link/up-link TTIs. (Subframe 1, 5, 6, 10 are configured as down-link subframes, subframe 3, 4, 8, 9 are configured as up-link subframes and subframe 2, 7 are configured as special subframe.) The duration of each VoIP service and Video service are both 150 seconds. In addition, the proportional fairness user schedule algorithm is chosen.

Definition 3 (Prediction Deviation [4]): The prediction deviation of the relative interference intensity of the communication link between UE $i$ and its interfering FAP $k$ is the absolute value of the difference of the predicted order number $o(i, k)_{pre}$ and the real order number $o(i, k)_{real}$. The $o(i, k)_{pre}$ is acquired from Algorithm 1 and the $o(i, k)_{real}$ is calculated based on the relative interference data collected from the LTE-Sim platform.

$$\delta(i, k) = |o(i, k)_{pre} - o(i, k)_{real}| \quad (7)$$

Fig. 5 shows the prediction deviations of the relative interference intensities of the communication links between each UE and each of its interfering FAPs. The abscissa represents...
the 15 interfering FAPs of each user where 1 corresponds to the strongest interfering FAP and 15 corresponds to the weakest interfering FAP. The ordinate indicates the identification of the users where 1 represents UE 1 and 16 represents UE 16. More specifically, $\delta(5,16) = 1$ represents that the prediction deviation of the fifth severest interfering FAP of UE 16 equals 1. It can be learnt from Fig. 5 that the proposed relative interference intensity modeling approach could achieve a high accuracy especially for the severe interfering sources. It is because the prediction deviations shown in Fig. 5 are small and most of the prediction deviations of the severe interfering FAPs equal 0.

Fig. 6 shows the cumulative distribution function (CDF) curves of the prediction deviations of the relative interference intensities of the communication links between all users and its interfering FAPs under the condition that the 5/10/15 severest interfering sources are considered. The abscissa represents the prediction deviation values. A conclusion could be drawn from Fig. 6 that the prediction deviations decrease when the number of the considered strongest interfering FAPs decreases because there are more large prediction deviations when more severe interfering FAPs are considered. The network performance is mainly impacted by the severe interference; thus, the modeling accuracy of the severe interference could be more important. The proposed approach could achieve an extremely high accuracy when the 5 strongest interfering FAPs are considered because there are only 6.25% prediction deviations equal to 1 and no larger prediction deviations.

Fig. 7 shows the average prediction deviations of all users versus the number of FAPs. Therefore, the proposed relative interference intensity modeling approach could be applied to the networks with larger scale.

Fig. 8 shows the average prediction deviations of all user versus the average TTI number $T$ when the 5/10/15 strongest interfering FAPs are considered. It could be concluded that the average prediction deviation of all user decreases with the increase of $T$ when the average TTI number $T$, which is related to the CQI value in Fig. 2, is smaller than 10. In addition, when the average TTI number $T$ is larger than 10, the curves fluctuate slightly and almost constant. Therefore, the
average TTI number $T$, which is used to derive CQI value, is more appropriate to be set as 10 such that both the prediction deviation and the computational complexity are both very low.

The benchmark algorithms used in Fig. 9 and Fig. 10 are three representative coloring methods published in recent studies. All of them are implemented based on the conflict graph of the network. For “Coloring method 1 [31]”, the heuristic algorithm proposed by Brélaz [32] is adopted. In [31], the vertex which is adjacent to the greatest number of differently colored neighbors is colored, with a new color if necessary (until colors are exhausted). Some users may failed to be colored with “Coloring method 1”, which could cause severe limitations on the network performance. For “Coloring method 2 [18]”, the conflict graph is colored based on the degree of saturation algorithm (DSA) first. The vertexes (i.e., users) with the same color are put into the same cluster and could reuse the same spectrum resources. Then, allocating spectrum resources to each cluster based on the ratio of the user number of each cluster to the total user number in the network. For “Coloring method 3 [33]”, if the sub-channels that haven’t been allocated by UE $i$’s neighbors (i.e., the UEs connected with UE $i$ in the conflict graph) are available for UE $i$, allocate such sub-channels to UE $i$ until the spectrum resource requirement of UE $i$ has been satisfied. If such sub-channels are unavailable, a new sub-channel will be added to the sub-channel set, which leads to the decrease of the bandwidth of each sub-channel. The actual spectrum resources allocated to a cluster depends on the average bandwidth requirements of that particular cluster. The “coloring method 1” and the “coloring method 3” are multi-coloring methods. The RB number required by each user in each TTI of these benchmark algorithms is also calculated as equation (4).

Fig. 9 shows the system spectral efficiency versus the network load when the number of FAPs is fixed at 128 (i.e., the deployment of FAPs is ultra-dense). It could be concluded that the spectral efficiency of the proposed load-aware approach outperforms than all the benchmark algorithms when we change the network load from 10% to 100% gradually. The simulation results verify that the proposed method could adjust the maximum orthogonal range based on the network load, and could make the appropriate RB allocation decisions for each UE according to the network load in the resource allocation process such that severe interference could be mitigated and the performance could be improved in the network. (The “Coloring method 2” distributes the spectrum resources based on the user number in each cluster without considering the requirements of UEs which determine the network load; thus, the simulation results of “Coloring method 2” remain constant in Fig. 9 when the network load is changed gradually.)

Fig. 10 shows the system spectral efficiency versus the number of FAPs in the network when the network load is fixed. The proposed load-aware method is compared with three representative coloring methods published in recent studies. It is obvious that the spectrum efficiencies of the proposed load-aware approach outperforms than all the benchmark algorithms when we increase the number of FAPs (i.e., enlarge the scale of the network). Especially, when the network load is 30% and there are 128 FAPs in the network, the proposed method outperforms than the Coloring methods 1/2/3 up to 43.88%, 62.00% and 88.86%, respectively. In addition, we perform such simulations under 50%, 70% and 90% network load as well. It could be known that the proposed method could achieve a higher performance than all the benchmark methods under most network densities especially when the network load is heavy and the network is ultra-dense. The simulation results validate that the proposed RB allocation algorithm could help to eliminate severe interference among users by finding the appropriate orthogonal interfering source set of each user, and allocating orthogonal RBs to UEs within this set to mitigate severe CCI and reusing common RBs with UEs beyond this set to increase spectral efficiency.

## VII. Conclusion

In this paper, a practical association rules based relative interference intensity modeling method and a load-aware resource allocation method is proposed, which could be used to improve the performance of the UDNs with the higher data rate requirement and time-varying network load. Simulation results show that the former possesses an extremely high accuracy and the latter eliminates severe interference efficiently, which provides a novel solution to the interference management problem in the load-varying networks.

In the future, we will focus our work on finding the proportional relations of interference coming from different interfering sources based on these data. The proportional relations not only include the information of which interference is stronger or weaker (i.e., relative interference intensities) but
also include the information of how much stronger or weaker a certain interference is comparing with other interfering sources. Apparently, the proportional relations include more specific information of the network interference condition, which could be more helpful in eliminating severe interference when allocating spectrum resources. Another issue we should consider in our future work is how to use other associated data to make an equivalent substitute when some data used in this paper couldn’t be obtained easily.

REFERENCES


Fig. 10. The system spectral efficiency versus the number of FAPs


