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Data-Driven Deployment and Cooperative Self-Organization in Ultra-Dense Small Cell Networks

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***Abstract*—Ultra-dense small cell network is widely acknowledged as a key enabler for high capacity wireless networks. Some of the key challenges that ultra-dense networks face are profitable deployment distribution under complex traffic loads and efficient radio resource management (RRM) in excessive interference environments. Poor small cell deployment locations can lead to excessive interference without clear profit margins and inefficient resource utilization. As such, data-driven small cell deployment and self-organizing RRM of small cell clusters are regarded as the two main technologies that can improve ultra-dense small cell services. This paper first reviews the latest research in data-driven small-cell deployment using structured and unstructured social media data. A combination of irregular clustering techniques is used to identify hotspots and natural language processing algorithms are used to identify blackspots. The paper then reviews recent advances in self-organization of small cell RRM and analyzes how data can improve self-organization performance. Moreover, the idea of cooperative self-organization is introduced to further promote the self-organization capability. Finally, two ultra-dense small cell RRM case studies are presented to demonstrate the performance improves of cooperative self-organization.**

I. Introduction

In the past decade, human civilization has seen unprecedented levels of urban migration and labour force mobility. The growing penetration of smart devices and wearable devices has meant that networks are experiencing exponential traffic demand growth per user and a compounded growth per coverage area. In order to meet the growing demand density in urban areas and in particular indoor areas, integrating heterogeneous cellular networks as well as WLAN access points is becoming an increasingly popular solution. Especially, in ultra-dense deployment scenarios, small cells can leverage on low transmission power, higher order modulation coding transmission and enable fine-grained spatial spectrum reuse, which can effectively promote the efficient utilization of spectrum. For these reasons, the ultra-dense small cells could meet both the connections and bandwidth requirements of hotspot scenarios, such as dense residences, business centers and large stadiums. It is anticipated that ultra-dense networks will cover most urban indoor and outdoor areas with small cells providing cell edge data rates of 100 Mbps to everyone [1].

Although the idea of ultra-dense small cell network promises us an attractive prospect, exploiting its potential advantages is heavily dependent on the radio resource management (RRM). Two distinct deployment features makes the RRM complicated: (1) commercial-guided ultra-dense deployment of clustered small cells in outdoor/indoor environments, and (2) the user-guided deployment of closed access small cells.

We can regard the goal of RRM as matching the traffic demand distribution and the radio resource distribution of all ultra-dense small cells. Due to the ultra-dense as well as hybrid deployment features, bridging the gap between the traffic demand distribution and the radio resource distribution faces crucial challenges. For the radio resource spatial distribution, the small cells are severely coupled because of increased interference. The negative effect of dense deployment is the massive interference relationship of small cells, which makes the spacial spectrum reuse challenging. For the traffic demand distribution, users' quality of experience (QoE) are also coupled [2] due to the sharing feature of both radio access capacity and backhaul bandwidth in a cell.

Small cell deployment and self-organization within small cell clusters are two keys to solve the above challenges. At the macroscopic level, cell deployment determines the spatial distribution of infrastructures, essentially playing an important role in optimizing the large-scale radio resource distribution. At the microscopic level, the self-organization further enables cells to tune the matching of traffic demand distribution and radio resource distribution in a finer level. The increasing availability of big data and machine learning algorithms further motivates us to examine the data-driven cell deployment and self-organization aspects of research. Currently, there has been very little or no work on how social media data can drive small cell adaptation. Social media data is more encompassing than traditional signaling data on networks, because it is: a) accurately geo-tagged, b) high dimensional (context includes topic, language, relations, and numerics), and c) network neutral (not biased towards a network service). As such, this more universal representation of human behaviour has the explainable power to better inform traffic patterns and

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drive dynamic small cell reconfiguration than standard network signaling.

In this paper, we first review the topics in data-driven cell deployment and data-driven self-organization, respectively. Then, we propose a simple but effective idea of cooperative self-organization, aiming to further promote the self-organization capability in ultra-dense small cell network. Finally, we present two use cases of cooperative self-organization and conclude this paper.

II. Data-Driven Cell Deployment

Over the past few years, large volumes of data has been transforming businesses to deliver higher precision and more personalized services. Fine-grained traffic data can transform the business model of cellular network operators by enabling the deployment of small-cells. Historically, Call Detail Record (CDR) based research (see Fig.1a-i), has yielded useful macroscopic statistical models on the spatial-temporal pattern of traffic demand. For example: the number of active users in a BS is $\sim$ Pois(.) distributed and the 3G traffic demand per user session is $\sim$ Log-N(.) distributed [4]. As operators seek to deploy small-cells to efficiently scale the overall network capacity and target traffic hotspots or signal blind-spots, there is a need to move from macroscopic traffic models to microscopic traffic modeling.

Small-cell deployment needs to consider a number of important parameters: 1) high resolution traffic demand data over a small coverage radius (10-25m), 2) high resolution consumer satisfaction or QoE, 3) high resolution indoor-outdoor (I-O) signal propagation modeling that is sensitive to building architecture and materials (see Fig.1b-i), and 4) interference with adjacent heterogeneous network cells (see Fig.1b-ii). The research on challenges 1) and 2) has received increasing attention with the proliferation of geo-tagged online-social-network (OSN) data (see Fig.1a-ii). This research is crucial to the economic feasibility of the small-cell business and replaces or supplements traditional CDR data based cell planning. The advantage of using social media data over operator's own data are as follows: 1) it can discover the overall traffic demand across all wireless networks and operators (i.e., the whole market, as opposed to its own), 2) it can uncover textual data about how people feel about various aspects of service, and 3) it provides real-time analysis for various SON operations.

A. Traffic Hotspot Detection using Irregular Clustering

In terms of traffic demand, the authors in [5] have shown that the large volumes of real-time Twitter data allows for a scalable way to create accurate maps of mobile data demand. In order to identify traffic hotspots, clustering of user data should consider contextual information and the irregular radio propagation environment. Current geometric cluster filters (e.g., Gaussian) are not suitable for urban small-cells, where obstacles highly impact cell coverage areas and appropriate ray-tracing or propagation data informed irregular clustering is needed to yield accurate hotspot detection (see Fig.1a-iii). Given the big data nature of the problem, appropriate computationally efficient clustering techniques with urban radio fitted irregular geometries should be considered, such as density-based spatial clustering of applications with noise and gradient based visit extraction.

The methods presented in this paper such as NLP and statistical analysis are reasonably social media platform neutral. There is no reason why we can't perform clustering or language analysis on an alternative social media platform if one was made available at the same scale as Twitter. We use Twitter to demonstrate results only, as it is one of the most successful social media services and has enjoyed continuous growth. It's open API approach is one of the few social media sites that allows data mining at the global scale (its international outreach is stronger than context specific alternatives like Flickr or FourSquare). Whilst it is true that the usage level varies between countries, it remains by far the most dominant data source for both academic research and industrial data analytics.

Preliminary results using Twitter data and various clustering techniques have shown that there is an empirical relationship between the number of Tweets and the data demand is found for uplink and downlink channels, which enables accurate forward traffic prediction up to 2 hours on the same day and for the same time period over the following 1-2 days. The relationship between estimated traffic load $\hat{r}$ (kbps) and the Twitter activity level n (Tweets/s):

$$\log_{10}(\hat{r}_i) = a_i \log_{10}(n) + b_i, \tag{1}$$

where the subscript i represents uplink "UL" or downlink "DL", ($a_{\text{UL}} = 0.86$ kb/Tweet $b_{\text{UL}} = 1.97$ kbps) for uplink transmission case and ($a_{\text{DL}} = 0.88$ kb/Tweet, $b_{\text{DL}} = 2.37$ kbps) for downwlink transmission cases.

B. Service Blackspot Detection using Natural Language Processing

In terms of QoE blackspots, these small areas of poor signal coverage or service delivery can lead to customer complaints and loss in business revenue. Understanding their spatial-temporal patterns at a high resolution is important for interventions, such as small-cell deployment. Conventional methods such as customer helplines, drive-by testing, and network analysis tools often lack the real-time capability and spatial accuracy required. In the recent study (see Fig.1b-iii) [6], the potential of utilizing geo-tagged Twitter data to uncover and classify blackspots was shown. Two natural-language-processing (NLP) techniques of lexicon and machine-learning (see Fig.1a-iv) were applied to over 1.4 million Tweets in London to uncover blackspots and categorize fault reports for both pre-4G (2012) and post-4G (2016) roll-out. For example, it was found that long-term *poor signal* complaints make up the majority of complaints (86%) pre-4G roll out, but short-term *network failure* was responsible for most complaints (66%) post-4G roll out. These methods combined can lead to more holistic small-cell roll out in complex urban environments (see Fig.1b-iv).

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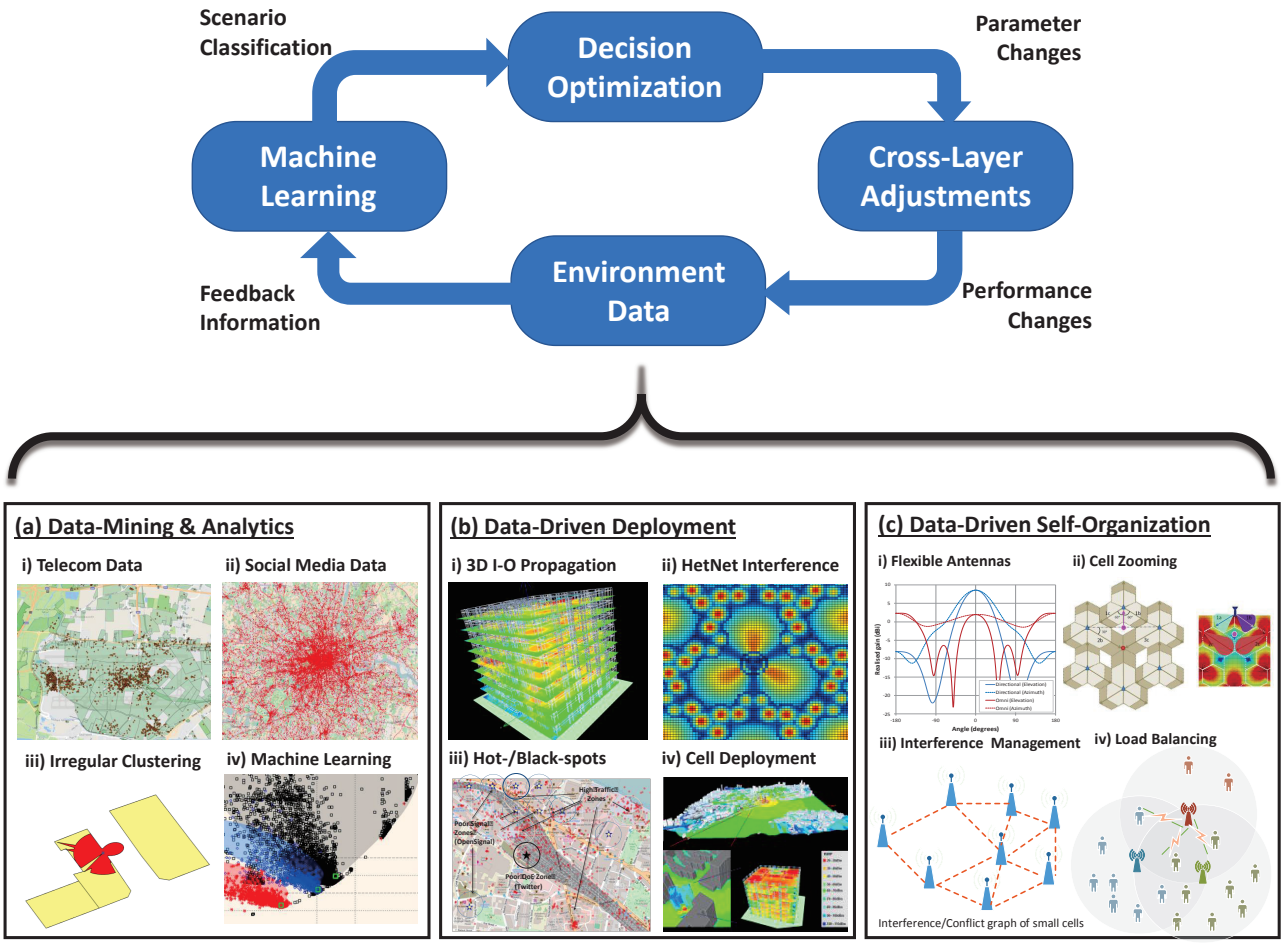

Fig. 1. Essential Technologies for Data-Driven Networks: (a) The structured and unstructured big data analysis of heterogeneous data will yield new insights into traffic hotspots and consumer experience blackspots; (b) The data analytics combined with propagation and HetNet interference modeling drive a new generation of ultra-dense small cell deployment processes; (c) The cells are built to be flexible to data-driven self-organization across multiple radio layers.

III. Data-Driven RRM Self-Organization

Once the cell deployment is finished, the RRM would play the role of adjusting radio resource distribution according to actual traffic demand distribution in a finer level. Since small cells are likely to be plug and play devices deployed by operators/users in an uncoordinated manner, self-organization mechanisms are preferred instead of conventional planning. The self-organization enables small cells to optimize their configurations independently and autonomously, either in a centralized or distributed manner. In centralized organization, a SDN server would gather all small cells' information and optimize their configurations with global information, which is attractive from both a computational efficiency and a security perspective. However, centralized SDNs may incur excessive information exchange costs (e.g. latency is undesirable for tactile applications). On the other hand, in distributed self-organization, small cells could adapt their parameters based on local sensing of environment in terms of network, traffic and channel fluctuations, which is more robust to network topology and scalable with increased message exchange costs than centralized SDNs. Reinforcement learning for online sequential decision making in dynamic and uncertain environments (e.g, Q-learning and automata in Markov Decision Processes) and game-theoretic distributed learning for multi-agent interactions (e.g, no-regret learning and stochastic learning automata) are two types of widely used algorithms.

For cell self-organization, additional data can contribute on two aspects: 1) it helps us to better understand the learning problem model and 2) it could enhances the learning algorithms. In the former case, the statistical traffic demand distribution derived from telecom data and social media data can more fully characterize the considered problem. Hence, the potential properties and constraints can be revealed and explicitly considered in self-organization problem formulation. In the latter case, apart from the naive feedback of cost (e.g.,interference) and reward (e.g., achieved throughput), various data can provide prior knowledge or comprehensive user feedback to improve the learning efficiency, as shown in Fig. 1. The input data in learning module can be long-term (e.g., the spatial-temporal traffic distribution law), medium-term (e.g., context information about traffic, application, user demand, scenario and so on) and short-term (e.g., interference, achieved performance/user QoE, channel and network dynamics). We briefly introduce several most crucial self-organization issues

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in ultra-dense small cell network in the following.

A. Antenna Configuration

A challenge faced by wireless networks is the growing data volume and associated energy consumption. How to meet a dynamic traffic demand at a consistently low energy consumption level is of importance from both commercial and climate change perspectives. What has been lacking is an integrated system that demonstrates how flexible radio front ends can be driven by real time data analytics. In the past few years, research teams have developed electrically reconfigurable directional to omni-directional antenna systems, which improves over mechanical flexible antenna systems (see Fig.1c-i). Feasibility studies have shown that such a dynamic base station can reduce the total operational energy of a cellular network by a peak of 75%.

Traffic distribution shows substantial fluctuations in space and time, especially for small cell network. For the same time duration, the small cells' loads of residential area and office area are diverse. For a given area, the small cells' loads may continuously evolve as time progresses. As a result, loads across small cells could be uneven and dynamic. Fixed cell coverage is no longer appropriate, while adjusting cells' power to form dynamic coverage is desired. Following this idea, a concept of cell zooming has been proposed, where small cells could sense the channel condition and load distribution and adjust their transmission power to zoom in for overloaded cells, zoom out or even go to sleep or switch off for cells under low load, whilst maintaining overall minimum coverage and QoS. Essentially, the traffic distribution fluctuation is resulted from user behaviors including mobility pattern and social interactions and etc. By understanding how user are spatially distributed, their QoS and QoE demand, the efficiency and accuracy of small cell zooming can be improved (see Fig.1c-ii).

B. Interference Management and Interference Model

Interference management is a key challenge in the small cell networks especially in ultra-dense scenario. Split-spectrum and shared-spectrum scheme are the typical two spectrum allocation schemes. For the split-spectrum scheme, small cells and macro cells operate on dedicated and orthogonal frequency bands; hence, the cross-tier interference management is significantly simplified. For the shared-spectrum scheme, small cells can reuse the macro cells' licensed frequency bands; therefore, the shared-spectrum scheme can achieve relatively higher spectrum utilization efficiency; while, the corresponding interference management is more complicated, since small cells may endure both co-tier and cross-tier interference from nearby small cell base stations and macro base stations, respectively. To tackle this issue, the interference management is implemented mainly through channel selection and power control of small cells.

There exist complex and coupled relationships among small cells from the perspective of both physical and social domains, which is related to the interference management. Generally, interference management self-organization works on the basis of some specific interference models such as binary interference graph or collision graph in the view of the media access control (MAC) layer (see Fig.1c-iii). The edges in binary graph can only characterize the pairwise relations and is not sufficient to modeling the cumulative interference, resulting by multiple weak interference sources, in dense networks. As a consquence, existing graph-based studies for resource allocation are mostly limited in the scope of relatively small-scale networks and cannot be directly extended to large-scale and ultra-dense scenarios. In the dense and heterogeneous wireless networks, the interference patterns tends to be more complicated since the received interference may generated from different network tiers or frequency bands with different access constraints such as in licensed sharing access (LSA) and LTE-U (LTE in unlicensed band) modes.

It is challenging to model the complicated interference relations of numerous communication entities in the context of ultra-dense communications. Recently, hypergraph theory is viewed as a powerful and promising mathematical tool to model the complicated relationship among multiple entities. Hypergraph is the generalization of conventional binary graph, where any subset of vertex set can form a hyperedge[1]. As pointed out in [12], hypergraph provides a more practical and tractable model to simultaneously represent strong and accumulative interference relations for ultra-dense networks consisting of numerous low-powered and small-coverage radio nodes [10], [11]. In Fig. 2, we present an illustration of hypergraph interference model. The hyperedges of cardinality 2 are represented as dash lines as similar as binary graph, and the elliptic curves represent the hyperedges of cardinality more than 2. For simplicity, we use HE 1-HE 7 to denote the corresponding hyperedges. We can observe that hypergraph can capture the cumulative interference effect caused by multiple weak interfering sources. Take HE 3 as an example, one of the vertex 7 and 6 can not be an independent interferer to vertex 1, but the co-channel concurrent transmission of vertex 7 and 6 may bring strong interference to vertex 1.

Constructing a fine-grained interference model, such as hypergraph interference model, needs data mining and analytic from large volume of context data for dense communications scenario. These collected context data includes radio environment characteristics, channel state information, transmission ability, receiver sensitivity, beam pattern, geographical location, *etc*. Some data operations are needed such as data cleaning and data completion in the construction and maintenance of the data-driven interference model. On the other hand, it is essential to timely update the data-driven interference model to fit the dynamic network topology; otherwise, the resource allocation strategy based on out-dated interference model will lead to low system utility.

C. Load Balancing

In the ultra-dense deployment scenario, there may be several available small cells in the vicinity of a user (see Fig.1c-iv), giving rise to the user-network association issue. The traditional received signal strength (RSS) based method has

[1]The edges in hypergraph are termed as hyperedges.

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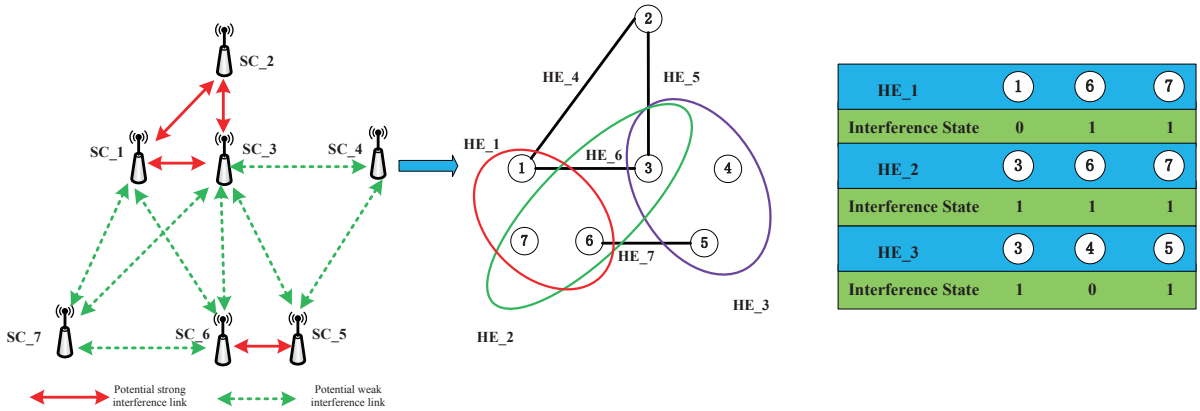

Fig. 2. Illustration of the hypergraph interference model. (a)The complicated interference scenario of ultra-dense small cells, where both potential strong and weak interference links exist. (b)By exploring context data, hypergraph can be constructed, where a hyperedge captures the cumulative interference effect caused by multiple weak interfering sources. Note that we only show partial weak interfering links that contribute to the construction of hypergraph.(c)We further introduce mark information to capture the asymmetric interference effect in hyperedges.

been a matter of concern, as both the radio access capacity and limited backhaul bandwidth of small cells could be the bottleneck of user experienced performance. Thus, both RSS and load should be jointly taken into account in cell selection and the network should balance the cell loads according to real-time user QoE and traffic load data. Two types of cell self-organization approaches are available to tackle this issue: network-assisted and network-controlled. In network-assisted approaches, the network will broadcast the load information of cells to assist the cell selections of users. In network-controlled approaches, the cells adjusts the user-network associations of all users in a proactive manner to achieve globally fair loads.

The aforementioned diverse small cell access choices also present new opportunities. For example, the association of a user to a single small cell limits its maximum achievable data rate to its backhaul capacity. A recent proposal in [8] demonstrated that a user can associate with multiple small cells in the user's local neighborhood. This scheme departs from the coordinated multi-point (CoMP) in that the user distributes his traffic load to several small cells on orthogonal frequencies. Moreover, this can also alleviate network congestion. To proactively enable the multiple association mechanism, two incentive mechanisms have been proposed. The first approach is encouraging residence users to open their small cells to all users. As residence owned small cells commonly work in closed access mode without cooperation, they are not fully utilized and may incur excessive interference to those outside the closed subscriber group. Once they are open to all users, they can effectively offload the load of overloaded public small cells. Of course, mobile operators have to provide appealing incentives to residence users and ensure their network and privacy security. Another approach is the user-in-the-loop approach [9], whereby coupled human-network controls are established in the form of:

- spatial control: encouraging users to move to a less congested service location,
- temporal control: encouraging users to reduce or postpone the current data demand in the event that the network is congested.

The potential incentives could be progressive tariffs, reward programs, higher access rates and so on. The challenge for these schemes are that they require to know both the real-time user traffic distribution and the global resource distribution data. Apparently, with these data, the cells could play a more positive role in load balancing through price, policy and some other mechanisms.

IV. Enhancing Self-Organization Through Cooperation of Neighboring Cells

A. Main Idea

The efficiency of distributed cell self-organization may be constrained by two aspects: limited information and excessive competition. On one hand, without additional supporters, each distributed cell only possesses its locally observed information (such as its achieved interference or throughput). The lack of some necessary data/information may constrain the ability of data-driven self-organization. On the other hand, individual self-organization in cells optimize their own performances, and as such, the self-interest and competition between multiple cells may lead to system instability and reduce system global performance. These motivate researchers to consider cooperative self-organization among cells. The introduction of cooperation in self-organization not only enables cells to share more data/information through X2 interface or cloud based message exchange, but also could achieve satisfactory balance between performance and system stability. In the following, we generalize the concept of cooperative self-organization and give a relatively formal formulation.

Let us consider a small cell network, whereby the goal of RRM is to maximize the sum of cells' performance. Specifically, given a small cell set $\mathcal{N}$, there is a relevant set of configuration parameter vectors $\mathbf{a}$ in the network. As such, the RRM optimization problem can be formulated as finding

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$\mathbf{a}^* \in \mathbf{A}$ to maximize the sum utility of all cells,

$$\arg\max_{\mathbf{a}\in\mathbf{A}} \sum_{n\in\mathcal{N}} f_n(\mathbf{a}) \tag{2}$$

where $\mathbf{a} = (\mathbf{a}_1, \mathbf{a}_2, ..., \mathbf{a}_N)$ is a configuration profile of all the small cells, $\mathbf{a_n} \in \mathbf{A_n}$ is the configuration of small cell n, $\mathbf{A} \subseteq \underset{n\in\mathcal{N}}{\times} \mathbf{A}_n$ is the set of available configuration vectors and $f_n(\cdot)$ is small cell n's utility function (e.g., key performance indicator (KPI)). For example, $\mathbf{a_n}$ can be user-network association profile, channel selection profile, joint spectrum and power selection profile, etc., $f_n(\cdot)$ could be the throughput or QoS related customized utility function. The above formulation is general enough to accommodate most RRM challenges that have deterministic KPI functions.

As in most distributed self-organization methods, each individual small cell n optimizes its own utility by selecting its configuration vector,

$$\arg\max_{\mathbf{a}_n\in\mathbf{A}_n} f_n(\mathbf{a}_n, \mathbf{a}_{-n}) \tag{3}$$

where $\mathbf{a}_{-n}$ is the configuration vectors of all cells except n, and $\mathbf{a} = (\mathbf{a}_n, \mathbf{a}_{-n})$.

In contrast, for cooperative self-organization, each individual small cell n selects its configuration vector to optimize the sum utility of its own and its spatial neighbor cell set $\mathcal{J}_n$ as

$$\arg\max_{\mathbf{a}_n\in\mathbf{A}_n} \sum_{m\in n\bigcup\mathcal{J}_n} f_m(\mathbf{a}_n, \mathbf{a}_{-n}) \tag{4}$$

The spatial neighborhood of n represents the cells that are coupled with cell n in the considered RRM issue. In other words, the configuration of n also affects the utilities of its neighboring cells. For instance, in interference coordination, the cells in the interference range of n are the neighbors of n.

B. Generalization

Although small cells are regarded as basic automatic optimization agents in the above formula, it can be easily extended to the case where a set of co-located cells that are jointly configured is regarded as a single automatic optimization agent and the spatial neighbors are the union of cell sets that are affected by the agent. Hence, the formula (4) can be extended as follows,

$$\arg\max_{\mathbf{a}_{set(c)}\in\mathbf{A}_{set(c)}} \sum_{m\in set(c)\bigcup\widetilde{\mathcal{J}}_{set(c)}} f_m\left(\mathbf{a}_{set(c)}, \mathbf{a}_{-set(c)}\right) \tag{5}$$

where $set(c)$ denotes some cell set c, $\mathbf{a}_{set(c)} = \underset{m\in set(c)}{\times} \mathbf{a}_m$ is the joint configuration vectors of the networks in $set(c)$ and $\mathbf{A}_{set(c)} \subseteq \underset{m\in set(c)}{\times} \mathbf{A}_m$, $\widetilde{\mathcal{J}}_{set(c)}$ is the spatial neighbour cell sets of $set(c)$, $\mathbf{a}_{-set(c)}$ is the joint configuration vectors of the networks in all sets except $set(c)$. Obviously, when the size of one cell set grows, the involved cells increases and the optimization complexity of the above formula increases, accordingly. The special case that the whole system constitutes the only cell set is exactly the centralized system-level optimization in formula (2). The special case that each single cell is a set is reduced to the cooperative self-organization in formula (4). In this sense, the cooperative self-organization realizes a trade-off between the fully distributed self-optimization and the centralized optimization.

The proposed cooperative self-organization ensures the system stability. By treating the cell sets as players, we can get a game $\mathcal{G} = \left(\mathcal{C}, \{\mathbf{A}_c\}_{c\in\mathcal{C}}, \{u_c\}_{c\in\mathcal{C}}\right)$, where each set c aims to optimize u_c, which is the same as the utility expression of formula (5). The game possesses the property that the change in any set c's utility resulted from its unilaterally deviating in $\mathbf{a}_{set(c)}$ accords with the change in the system-level goal as defined above. According to the potential game theory [13], the game $\mathcal{G}$ belongs to the exact potential game that was proved to have at least one pure strategy Nash equilibrium. In particular, the system-level goal is just the potential function, indicating that the global optimum solution is one of Nash equilibriums.

The proposed cooperative self-organization differs from CoMP on two aspects. On one hand, it is actually a general optimization scheme, which could be applied to different self-organization issues, such as spectrum allocation, user association, cell coverage *etc.*., and realized in different forms as mentioned in the examples and some related works. Although the CoMP shares a similar idea of base station cooperation, it mainly focuses on coordinating and improving the signal transmission and reception of UE. On the other hand, the optimization target of each cell in cooperative self-organization is the sum utility of itself and its neighboring cells; while there is not such an explicit goal for each cell in CoMP. On the cost of cooperation, the cooperative self-organization indeed requires data exchange between spatial neighboring cells, which would incur transmission overhead of backhaul links. The actual transmission overhead depends on the required information and iteration times of specific algorithm. Considering that the number of utility functions and configuration parameters are finite, the data exchange in each iteration between two cells are limited. Hence, the impact of transmission overhead on cells' performance is limited.

In Tab. I, we summarized some potential application scenarios of cooperative self-organization in ultra-dense small cell network RRM. Some related works that share the similar idea are also provided.

V. Use Cases

In order to motivate the readers, we now present two detailed use cases of cooperative self-organization for (1) spectrum sharing of LTE-U small cells and (2) user association.

A. Case Study 1: Spectrum Sharing

We consider the spectrum sharing in the ultra-dense LTE-U small cell networks. We randomly generate an ultra-dense small cell network consisting of 35 small cells in a given region. For simplicity, we assume that the number of available channels of small cells is 3 and each small cell only selects one channel for transmission. Small cells can access available channels in an *opportunistic and self-organized manner*. An improved *hypergraph interference model* with mark information is adopted to represent the complicated

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TABLE I
POTENTIAL APPLICATION SCENARIOS OF COOPERATIVE SELF-ORGANIZATION IN ULTRA-DENSE SMALL CELL NETWORK.

Application Scenario	Optimization Object	Spatial Neighborhood Set	Strategy	Related Works
Cell Sleep Mode	Energy consumption minimization/ Energy efficiency maximization, etc.	Neighboring small cells	Cell mode selection: active/sleep	Ref. [21]
Spectrum Sharing	Network capacity maximization/ Access collision minimization, etc.	Neighbors in the interference graph	Select one or more channels from available set	Ref. [11]
User Association	Users satisfaction (i.e. QoE) maximization/ Network capacity maximization, etc.	Cells with overlapping coverages	Select one or more networks from available set	Ref. [7]
Power Control	System interference level minimization/ Network capacity maximization, etc.	Neighbors in the interference graph	Transmission power level	Ref. [22]

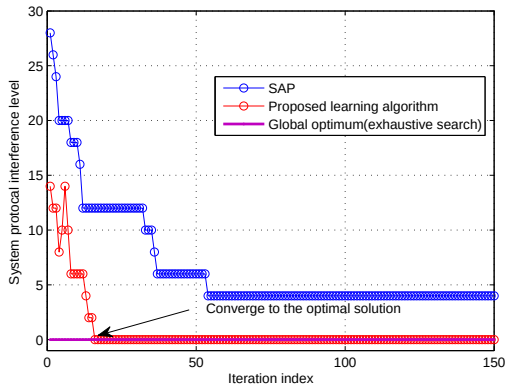

Fig. 3. Performance comparison of the proposed multi-agent learning with local cooperation.

interference relationship among small cells. Different from the existing hypergraph-based studies, we introduce extra mark information to capture the asymmetric interference effect in hyperedges for hypergraph interference model. Given a hyperedge, the small cell's interference state is marked as '1' if it is interfered by the co-channel transmission of all small cells involved in this hyperedge; otherwise, it's state is marked as '0'. In Fig. 2(c), we present an illustration of the hypergraph interference model with mark information for a small cell networks with 7 small cells.

In this scenario, the system-level optimization objective is to find an optimal channel allocation scheme *minimizing the network interference*, which is defined as the sum of all small cells' protocol interference level from the MAC layer. In the context of cooperative self-organization, each small cell's utility is the sum of its own and spatial neighbors' interference level following the form of (4). Specifically, spatial neighbor cell set $\mathcal{J}_n$ contains the small cells in the same hyperedges with cell n. As a consequence, we can prove that the spectrum sharing problem mentioned above can be formulated as a potential game and the optimal PNE corresponds to the optimal channel allocation. Spatial adaptive play (SAP) can approach the optimal PNE of the potential game with an arbitrarily high probability in an iteration and distribution manner [15]. We propose a multi-agent learning algorithm based on SAP to search the optimal channel allocation. The main idea of the proposed learning algorithm is to randomly choose multiple non-neighboring players at each learning iteration, rather than one player in SAP, to alter their actions in the hypergraph, so the proposed scheme owns a faster convergence rate.

At each learning iteration of the proposed learning scheme, multiple non-neighboring players are selected in the hypergraph. Then, these players exchange the local cooperation information, i.e. interference level, with their player-specific neighbors and update its channel selection strategy following the SAP rule. Until the maximum iteration number is reached, the learning algorithm stops. We compare our scheme with both SAP and the global optimum obtain by exhaustive search. The result in Fig. 3 shows the convergence performance of the proposed learning algorithm. We can find that the proposed algorithm can quickly search the optimal channel allocation solution which minimizes the system interference level.

B. Case Study 2: User Association

In this case study, users are randomly distributed in the coverage area of six partially overlapping small cells 1 6. The small cells are assumed to work on orthogonal frequency bands, *i.e.*, there is no inter-cell interference. The corresponding overlapping areas can be denoted by the sets of involved small cells as (1, 2), (2, 3), (3, 4), (4, 5) and (5, 6). We assume that each small cell has a fixed total $R = 50$ Mbps bandwidth and service differentiation with proportional fairness policy [16] is used. Specifically, the achieved throughput of each user is proportional to its weight in the same cell. The throughput of user k with weight w_k that is currently associated with small cell n is expressed as $\frac{w_k R}{\sum_{i \in \mathcal{I}_n} w_i}$, where $\mathcal{I}_n$ is set of users associated with small cell n. The user weight is assigned according to traffic type to differentiate traffic demand. Users fall into the following three types with equal probabilities: i) *brittle traffic users*, ii) *stream traffic users*, and iii) *elastic traffic users*; with user weights 1, 1.2 and 1, respectively. The brittle traffic user refers to real-time traffic with strict throughput requirements. There seems to be a throughput threshold beyond which the user has the maximal utility 1 and can not increase any longer. The stream traffic user also has a throughput threshold, but its utility grows gradually and approaches 1 when the achieved throughput is larger than the threshold. While the elastic traffic user has no throughput threshold and can benefit from any positive non-zero throughput, and its utility grows gradually and approaches 1 as the achieved throughput increases. Examples of the aforementioned non-real-time traffic types include E-mail or file transfer. The utility functions for these three traffic types can be found in [17].

The system-level objective is to find the optimal user-network association profile for users in the overlapping areas

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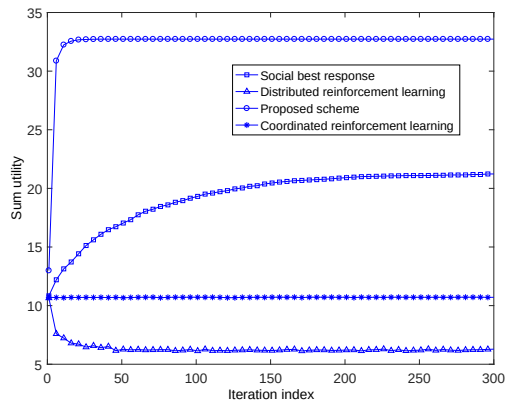

Fig. 4. Convergence comparison of different algorithms in the user-network association.

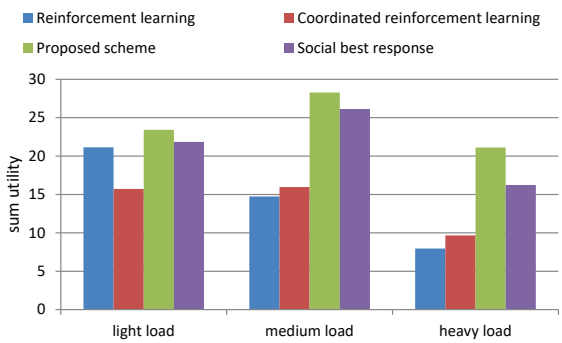

Fig. 5. Performance comparison of different algorithms in the user-network association.

of the small cells to maximize the total utility of users. We assume that each user must have at least one network associated. In the application of cooperative self-organization, each pair of partially overlapping small cells form a basic automatic optimization agent to cooperatively re-associate users in their overlapping area with the goal of maximizing the total utility of *users associated with them*. Since the associations of users in overlapping area do not affect other cells, there is no neighbor for each automatic optimization agent.

To tackle this problem, an iterative optimization algorithm in [7] is proposed. In each iteration, there are two steps:

1) An overlapping area is randomly selected;
2) The involved small cells are activated to optimize the association profile of users in the selected overlapping area, according to the real-time QoE data reported by all users.

We consider three approaches for comparison: 1) *Distributed Individual Reinforcement Learning* - each user adjusts the selected network to maximize the achieved utility, according to the reinforcement learning algorithm [18] [19], 2) *Social Best Response* - a randomly selected user is activated and deviates his small cell association to maximize the sum utility of all users in each iteration, and 3) *Coordinated Reinforcement Learning* - Under the framework of reinforcement learning, a marginal cost pricing is added in each user's utility to reflect the loss of throughput caused by his presence in the currently associated small cell. The algorithm detail can be found in [20]. The convergence result (averaged by 100 samples) of these algorithms in Fig. 4 indicates that the proposed scheme could converge fast and achieve the best performance. Under three different loads, the proposed scheme always achieves superior performance, as shown in Fig. 5. Due to user competition, the individual reinforcement learning is the worst in most cases, but offers the lowest computation and information sharing complexity. Although coordinated reinforcement learning and social best response are cooperative in nature, they offer poor computational efficiency and this is an area of open challenge.

VI. Conclusions and Challenges

This paper has reviewed the state-of-the-art practices in data-driven ultra-dense small cell deployment and self-organization. Deploying cells in traffic rich and poor service areas offers superior opportunities for business revenue and improved network resource utilization. The identification of traffic rich zones through spatial clustering and the categorization of poor service through natural language processing of social media data can dramatically improve over standard network data approaches. After deploying small cells in an ultra-dense cluster, cell self-organization is essential to reduce interference and improve capacity. Existing methods of individual and distributed self-organization is inefficient, and we show through two case studies how cooperative self-organization can lead to superior performances. The methods reviewed and results presented here offers new insight into how new developments in big data and machine learning can assist the small cell industry.

Many new challenges and opportunities still exist for the data-driven small cell deployment and RRM self-organization research areas. As heterogeneous big data becomes increasingly available at fine resolutions, the interaction between high dimensional data features and network parameters can potentially become too complex for human domain experts. New methods in machine learning, such as deep learning using convolutional neural networks [23] may become appropriate.

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