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A Load-Aware Clustering Model for Coordinated Transmission in Future Wireless Networks

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ABSTRACT Coordinated multi-point (CoMP) transmission is one of the key features for long term evolution advanced (LTE-A) and a promising concept for interference mitigation in 5th generation (5G) and beyond future densely deployed wireless networks. Due to the cost of coordination among many transmission points (TP), radio access network (RAN) needs to be clustered into smaller groups of TPs for coordination. In this paper, we develop a novel, load-aware clustering model by employing a merge/split concept from coalitional game theory. A load-aware utility function is introduced to maximize both spectral efficiency (SE) and load balancing (LB) objectives. We show that proposed load-aware clustering model dynamically adapts into the network load conditions providing high SE in low-load conditions and results in better load distribution with significantly less unsatisfied users in over-load conditions while keeping SE at comparable levels when compared to a greedy clustering model. Simulation results show that the proposed solution can reduce the number of unsatisfied users due to over-load conditions by 68.5% when compared to the greedy clustering algorithm. Furthermore, we analyze the stability of the proposed solution and prove that it converges to a stable partition in both homogeneous network (HN) and random network (RN) with and without hotspot scenarios. In addition, we show the convergence of our algorithm into the unique clustering solution with the best payoff possible when such a solution exists.

INDEX TERMS 5G, network MIMO, coordinated multi-point, SON, load balancing.

I. INTRODUCTION

Mobile data traffic has been growing rapidly and it is expected to grow at an annual growth rate of 46% over the next 5 years i.e. a 7-fold increase is expected by 2022 [1]. A 1000 times more capacity is envisioned for the next generation wireless networks: 5G [2]. Cell densification, additional spectrum and advanced interference mitigation techniques are proposed to meet this additional capacity challenge for 5G.

To achieve higher SE, CoMP or network multiple-input multiple-output (MIMO) is a promising concept which can mitigate inter-cell interference, even exploit the interference as useful signal. Multiple users are jointly served by a number of base stations (BS) in coordination, where scheduling/precoding functions are performed jointly, typically from a central CoMP control unit (CCU). CoMP is already a key feature, standardized for LTE-A, by third generation partnership project (3GPP) in Release 11 [3] and it is a promising concept discussed for 5G [2], [4].

Coordination between large number of BSs comes with its challenges such as high amount of data sharing (user data/channel state information (CSI)), precise synchronization for coherent joint transmission, complex precoding and scheduling design, additional signal processing etc. Due to these challenges, coordination can only take place within small clusters of cells. Hence network BSs need to be grouped into smaller clusters for CoMP. Efficient cluster design is a key factor to maximize the CoMP gain and achieve various network objectives like SE, energy efficiency and LB. An extensive survey on CoMP and clustering challenges is available in [5]. Network clusters need to be dynamic and adapt to changing network conditions and user profiles. Dynamic CoMP clustering is identified as a key concept for maximizing CoMP gains by adjusting network clusters dynamically to adapt into spatio-temporal

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changes in user/network profiles [5]. Static clusters will fail to provide optimum CoMP gains when network conditions or user concentration changes significantly in the network. Self-organized, dynamic CoMP clusters are also in paramount importance in the case of man-made or natural disasters where user density is populated in small areas and network infrastructure are partly damaged and not in service. CoMP clusters need to adapt to emergency network situation without manual intervention to provide optimum service possible with given changes.

There are mainly three different types of CoMP clustering studied in literature [5]:

1) **Network-centric clustering**: Cells are grouped into clusters where CoMP takes place within each cell cluster, i.e. users are assigned cells from within the cell clusters only. Users which are located at the cluster boundary will experience interference from cells outside of the cluster. This type of clustering reduces the additional overhead and complexity from CoMP, but CoMP gain is compromised due to inter-cluster interference.
2) **User-centric clustering**: There is no network-centric clustering, but users are allocated groups of cells for cooperation, so each user is provided its own user-centric cluster of cells. There is no limit on which cells to be selected for each user. This type of clustering maximizes the CoMP gain, however the CoMP overheads and complexity is very high.
3) **Hybrid clustering:** This type of clustering utilities both approaches above, employing a network-centric clustering to group cells into clusters first to reduce CoMP implementation complexity and overheads, and deploy user-centric clustering within each of the network-centric cluster where users are allocated their own individual group of cells within the network-centric cluster for cooperation. This approach provides a balanced approach where complexity/overheads for CoMP is reduced and CoMP gain is relatively high with user-centric clustering model operating within each network-centric cluster.

In this paper, we define LB as one of key objectives for CoMP clustering as CoMP is likely to deployed in areas where there is high concentration of users at different times, and LB is key to manage the high demand in specific areas. For the first time in literature, we design a network-centric clustering model where LB and SE are jointly optimized. We deploy a user-centric clustering model within the network-centric clusters to present a hybrid clustering model for a novel, low complexity solution. Related work in literature and the contribution of our work is further elaborated in the next section.

II. RELATED WORK AND PROBLEM STATEMENT

Network clustering challenge for CoMP attracted an extensive amount of research activity recently [5]. Li *et al.* [6] proposed a dynamic network-centric clustering algorithm to maximize cell throughput where users are proposed to be cooperating with two TPs only. Solution relies on exhaustive search for finding the best clusters to maximize the number of users with their preferred two cells in the same cluster, hence not scalable for larger networks. Limiting coordination to a fixed size (i.e. two) for each user can also lead to inefficient CoMP design in some scenarios where there is more than two cells serving in the area. In [7], a greedy algorithm is employed to form dynamic network-centric CoMP clusters with the aim of maximizing SE in uplink where a fixed maximum cluster size is proposed. Fixed cluster size leads to inefficiencies depending on the BS deployment density, where higher cluster size is required for dense deployment scenario to avoid inter-cell interference and maximize CoMP gains and lower cluster size is sufficient in more sparse deployment. Cluster size needs to be a dynamic parameter which should adapt to the density of the network. Moreover, depending on which cell the algorithm starts from, it ends up with a different clustering scheme which degrades the final design especially for a network with non-homogeneous user traffic. Moon and Cho [8] propose a cluster merge algorithm to maximize SE where every merge possibility is evaluated and cells are merged into clusters based on SE improvement. Unlike [7], clusters are formed around the much needed loaded areas first, however the solution is not scalable due to high complexity with large network size. This proposal again is limited to a static maximum cluster size. A distributed coalition formation framework using coalitional game theory is presented in [9] where a merge/split game is proposed for a distributed, low overhead cost cluster formation for users. Maximum cluster size is also dynamically allocated depending on the density of users. Although the proposed algorithm is a distributed one, it lacks on scalability for larger network size, as the number of possible merge operations increase with the network size. A similar approach is employed in [10], where BSs search for the best cluster to merge at regular time intervals. The solution also lacks on scalability similar to [9] and both solutions employ a capacity function as the utility which lacks on a comprehensive objective taking various network performance indicators into account. A holistic approach to CoMP clustering needs to combine multiple network objectives like load balancing, energy efficiency, backhaul optimization etc. alongside with SE and jointly optimise these key objectives.

A number of multi-objective dynamic clustering algorithms are studied in literature where energy efficiency and spectral efficiency are jointly optimized [11]–[13] and also backhaul availability is taken into account for clustering design [14]–[16]. However, to our knowledge, load balancing has not been considered in network-centric CoMP clustering in literature which jointly optimize LB and SE. Given that CoMP is likely to be deployed in interference-limited, dense deployment scenarios, there will be inevitably hotspot areas where some cells will be much more loaded than others at certain times of the day. Additionally, in the event of disasters, users will be concentrated in small areas causing high load on certain BSs. Autonomous LB solution is required to distribute the load and relieve congestion at hotspots without manual intervention. In the case of CoMP deployment, LB needs to be taken into account in a hybrid clustering solution where load-aware network-centric clusters are formed, and user-centric clustering is deployed within each network-centric cluster. There are few studies in literature which provide load-aware user-centric clusters. A user-centric clustering solution is provided in [17] for non-coherent CoMP scenario to jointly optimize LB and SE. In our recent work, we presented a load-aware, user-centric clustering algorithm [18] for multi-user (MU), joint transmission (JT) CoMP scenario where trade-off between LB and SE gain is studied. Both solutions suffer high complexity and increased CoMP overhead when CoMP is deployed within large number of cells. A load-aware network-centric solution is required to cluster the radio access network into small groups of cells where user-centric solution is deployed within each cluster. To our knowledge, there is no network-centric clustering solution studied in literature which takes LB into account.

In this paper, we attempt to fill the gap in literature and present a novel load-aware network-centric clustering algorithm where LB and SE objectives are jointly optimized. We formulate a merge/split coalition formation game to design load-aware clusters for DL MU-JT CoMP scenario. A load-aware utility is designed to formulate the trade-off between cluster size/complexity and SE/LB. A dynamic cluster size adaptation is formed where maximum cluster size is dynamically increased in high load conditions to improve SE and reduce load. We show that our proposed merge/split cluster formation framework provides a low complexity solution and always converges to a stable partition in both HN and RN scenarios with different load conditions. Moreover our load-aware clustering model achieve high SE in low-load scenario and better load distribution in high-load scenario resulting in lower number of unsatisfied users while keeping SE at comparably high levels. We analyze the trade-off between additional complexity of bigger cluster size and the improvement in SE and LB in both HN and RN scenarios. Simulation results are compared to an improved version of greedy clustering model presented in [7].

In this context, the unique contribution of this paper is that we introduce LB as one of the key objectives for network-centric clustering for the first time in literature and develop a novel, low complexity and stable network-centric clustering model as a first attempt to fill the gap in literature for load-aware network-centric CoMP clustering, jointly optimizing LB and SE.

The rest of the paper is organized as follows. In Section III, we present our system model for MU JT-CoMP and discuss key performance metrics and overheads for CoMP. In Section IV, we first present coalition formation game concepts. Next, we introduce our SE-based and load-aware utility functions employed in our coalitional game. We then present merge/split game operation in detail and discuss its complexity and stability. In Section V, we present simulation results for HN and RN with and without hotspot scenarios. Finally, conclusions are drawn in Section VI.

III. SYSTEM MODEL

A. NETWORK MODEL

Consider a heterogeneous network (HetNet) scenario where there is one macro base station (MBS), N small cells (SC) and K users which are distributed within the coverage area of the MBS. The SCs are connected to the MBS with fast fiber backhaul links where all SCs share their CSI with MBS. Similar to the approach taken by 3GPP scenario in [19], a designated frequency spectrum is assumed at each layer, hence no interference is expected between MBS and the SC layer.

MU-JT CoMP is employed at SC layer where user data is made available in all SCs within the same network-centric cluster. Network-centric clustering and associated precoding/scheduling is performed at CoMP control unit located at the MBS. We propose that re-clustering activities don't aim to exploit the fast fading changes (i.e. in miliseconds) but it will respond to spatio-temporal changes in user/demand profile and the network. Hence, we propose re-clustering activity at a slower rate i.e. in seconds/minutes where fast fading changes are averaged out within this time window. This provides extra resilience in clustering decisions to issues like imperfect CSI knowledge and also reduce the additional signaling required for faster re-clustering [20]. Precoding within the cluster takes place at much faster rate (i.e. in milliseconds) where fast fading changes are exploited. We assume ideal backhaul and perfect CSI knowledge where intra-cluster interference is reduced to negligible levels with a typical precoder like zero forcing (ZF) precoder. Similar assumptions are made in other clustering works such as [7], [21].

Assume that the SC layer is partitioned into smaller clusters of SCs $C = \{C_1, \ldots, C_s\}$ and users are assigned to each SC cluster forming user clusters $U = \{U_1, \ldots, U_s\}$ i.e. user group U_i is assigned to SC cluster C_i. Suppose any user $UE_k \in U_i$ is assigned a network-centric cluster C_i and a user-centric cluster of C_i^k where $|C_i^k| = T$ and $C_i^k \subseteq C_i$. Let U_i^k be the group of UEs including UE_k which are scheduled at the same physical resource block (PRB) in C_i^k where $|U_i^k| = R$. We assume one antenna for each SC and UE for simplicity. A $T \times R$ virtual MIMO system is formed with C_i^k SCs and U_i^k UEs.

For each UE in U_i^k, received signal can be expressed as:

$$\mathbf{y} = \mathbf{HWx} + \mathbf{n}, \mathbf{H} \in \mathbb{C}^{R\times T}, \mathbf{W} \in \mathbb{C}^{T\times R} \tag{1}$$

where channel matrix $\mathbf{H} = \left[\mathbf{h}_1\mathbf{h}_2 \ldots \mathbf{h}_R\right]^T$
and channel vector at UE_k is expressed as:

$$\mathbf{h}_k = \left[h_{k1}h_{k2} \ldots h_{kT}\right] \tag{2}$$

Precoding matrix $\mathbf{W} = \left[\mathbf{w}_1\mathbf{w}_2 \ldots \mathbf{w}_R\right]$
and beamforming vector for UE_k is expressed as:

$$\mathbf{w}_k = \left[w_{1k}w_{2k} \ldots w_{Tk}\right]^T \tag{3}$$

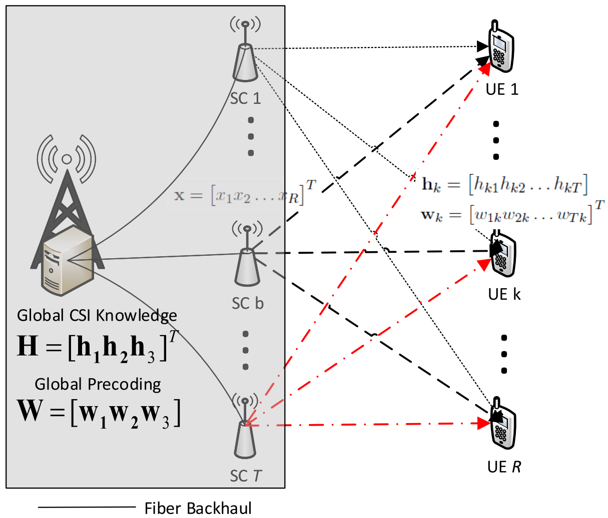


FIGURE 1. System model for downlink MU JT-CoMP.

An illustration of the system model is shown in Figure 1. Received signal at UE_k is:

$$y_k = \mathbf{h}_k^{\mathcal{C}_i^k} \mathbf{w}_k^{\mathcal{C}_i^k} x_k + \sum_{i \in \mathcal{U}_i^k/k} \mathbf{h}_k^{\mathcal{C}_i^k} \mathbf{w}_i^{\mathcal{C}_i^k} x_i + \sum_{j \in \mathcal{K}/\mathcal{U}_i^k} \mathbf{h}_k^{\mathcal{N}/\mathcal{C}_i^k} \mathbf{w}_j x_j + n_k \quad (4)$$

First term in (4) is the desired signal, where the second term is the intra-cluster interference from SCs within the cluster $\mathcal{C}_i^k$ followed by inter-cluster interference from SCs outside of the cluster $\mathcal{C}_i^k$. The last term n_k is the additive Gaussian white noise (AGWN) at UE_k.

SINR at UE_k can be expressed as:

$$SINR_k = \frac{|\mathbf{h}_k^{\mathcal{C}_i^k} \mathbf{w}_k^{\mathcal{C}_i^k} x_k|^2}{\sum_{i \in \mathcal{U}_i^k/k} |\mathbf{h}_k^{\mathcal{C}_i^k} \mathbf{w}_i^{\mathcal{C}_i^k} x_i|^2 + \sum_{j \in \mathcal{K}/\mathcal{U}_i^k} |\mathbf{h}_k^{\mathcal{N}/\mathcal{C}_i^k} \mathbf{w}_j x_j|^2 + |n_k|^2} \quad (5)$$

Intra-cluster interference term $\sum_{i \in \mathcal{U}_i^k/k} |\mathbf{h}_k^{\mathcal{C}_i^k} \mathbf{w}_i^{\mathcal{C}_i^k} x_i|^2$ in (5) becomes negligible when a typical precoder like ZF precoder is employed at the CCU with perfect channel knowledge. We assume equal transmit power on each physical resource and also equal total transmit power for each SC. Average SINR term is employed for clustering algorithm as discussed in the previous section. The complex fast fading channel coefficient of the path loss is averaged out in average SINR term and hence, $SINR_k^{aver}$ can be simplified as:

$$\hat{SINR}_k^{aver} = \frac{P_{Tx} \sum_{i \in \mathcal{C}_i^k} |g_{ki}|^2}{P_{Tx} \sum_{j \in \mathcal{N}/\mathcal{C}_i^k} |g_{kj}|^2 + N_0 B_{tot}} \quad (6)$$

where N_0 is the noise spectral density, B_{tot} is the total system bandwidth and g_{ki} is the distance based path-loss and shadow fading component.

Any user UE_k is first assigned a network-centric cluster $\mathcal{C}_i$ and a user-centric cluster $\mathcal{C}_i^k$ is formed for UE_k from SCs within $\mathcal{C}_i$ based on average received signal level. Inspired from our previous work in [18], 2 simple conditions are followed to form user-centric cluster $\mathcal{C}_i^k$ from $\mathcal{C}_i$:

1) Average received power level at UE_k from SC_j in $\mathcal{C}_i^k$ (P_{kj}^{rx}) should be greater than a minimum threshold i.e. $P_{kj}^{rx} > P_{min}$. This eliminates any SCs which dont provide the required level of coverage to UE_k.
2) The difference in average received power from the best serving SC_m (P_{km}^{rx}) to SC_j within $\mathcal{C}_i^k$ should not be greater than a treshold i.e. $P_{kj}^{rx}/P_{km}^{rx} > P_{\Delta}$. This ensures only SCs with similar received power levels are in the cluster to maximize interference cancellation from CoMP and prevent unnecessary addition of SCs in $\mathcal{C}_i^k$.

User-centric clusters $\mathcal{C}_i^k$ always have best serving SC and other SCs in the cluster based on above 2 rules. In this study, we design a network-centric clustering model to jointly optimise LB and SE, but load balancing within the network-centric clustering by adjusting user-centric clusters $\mathcal{C}_i^k$ is out of scope for this work. A detailed load-aware user-centric clustering model is presented in our previous work in [18].

B. COMP PERFORMANCE AND OVERHEAD METRICS

The key performance metric for CoMP is the SE improvement achieved by interference mitigation. SE improvement leads to less radio resources utilised, and hence lower cell load. More SCs within the same cluster $\mathcal{C}_i$ will provide additional interference cancellation and better SE, but on the other hand, increasing the cluster size will increase the CoMP overheads. Additional pilot channels are required for CSI estimation as cluster size increase, hence reducing the resources available for user data. Moreover, precoding computation gets more complex and additional backhaul badwidth is required as the cluster size increase. In this section we formulate CoMP performance and overhead metrics to deploy in the our dynamic clustering problem.

1) CELL LOAD

Cell load can be interpreted as one of the key metrics to quantify CoMP gain and cost trade-off. As CoMP cluster size increases, interference from more cells are mitigated, and hence SE is improved further which then reduces the cell load. On the other hand, with increased cluster size, more pilot resources are required for channel estimation which will reduce available PRB bandwidth for user data. This will then derive the load higher due to reduced PRB bandwidth.

Cell load can be defined as the ratio of required PRBs for all users associated to the cell against the total available PRBs. We first define the average required PRBs for each UE_k at each cell. In no CoMP scenario, assuming constant guaranteed bit rate (GBR) requirement d_k for UE_k, average PRB requirement for UE_k can be expressed as $r_k = d_k/(y_k B_{PRB})$ where $y_k = log_2(1 + \hat{SINR}_k^{aver})$ and B_{PRB} is the total bandwidth for user data in a single PRB. In MU

JT-CoMP, UE_k requires resources from all SCs within its user-centric cluster C_i^k, and PRB resource for UE_k is shared between all users in U_i^k which are scheduled within the same cluster. We assume $|C_i^k| = |U_i^k| = n_k$ and define "virtually" dedicated PRBs for UE_k at each SC within C_i^k as $\hat{r}_k = r_k/n_k)$ [18].

Assume that SC_m is in coalition C_i and $\mathcal{U}_{im}$ is the associated active UEs in SC_m where $U_{im} \subseteq U_i$ i.e. SC_m is not connected all users in U_i due to user-centric clusters of some users may not include SC_m. Let R_{tot} be the total number of PRBs for each SC, assuming all SCs have same total bandwidth. Cell load on SC_m in coalition C_i can be expressed as:

$$\hat{l}_{im} = \frac{\sum_{k\in U_{im}} \hat{r}_k}{R_{tot}} \tag{7}$$

2) UNSATISFIED USERS

Based on cell load $\hat{l}_{im}$ and the number of connected users U_{im} at each SC, we further define an unsatisfied users metric to quantify the impact of load in users. For a given GBR requirement for each user d_k, we denote users as "satisfied" if they achieve their GBR, otherwise unsatisfied. Intuitively, if $\hat{l}_{im} < 100\%$, all users are satisfied and if for example $\hat{l}_{im} = 300\%$ then one third of the associated users are satisfied [18], [22].

In MU JT-CoMP scenario, users are connected to more than one SC, hence associated connected user count for each SC will need to be adjusted for CoMP scenario to avoid double-counting. We define a "virtually dedicated" user count for each SC by distributing the number of users to each SC within its user-centric cluster. Assume UE_k has user-centric cluster of C_i^k with $|C_i^k| = n_k$. We define the "virtually dedicated" user count at SC_m in coalition C_i as $\hat{u}_{im} = \sum_{k\in U_{im}} 1/n_k$.

Unsatisfied users for each SC in C_i can then be expressed as [18]:

$$z_{im} = \max\left(0, \hat{u}_{im}\left(1 - \frac{1}{\hat{l}_{im}}\right)\right) \tag{8}$$

3) ADDITIONAL PILOT OVERHEAD

One of the challenges for CoMP is the requirement for additional pilot channels for CSI estimation in downlink as the number of TPs in coordination increases [23]. Using the optimum pilot overhead estimation for multi-antenna channels in [23]:

$$\begin{aligned}\alpha = &\sqrt{(1+SNR)\frac{\dot{C}(SNR)}{C(SNR)}2n_T f_D} \\ &- \left((1+SNR)\frac{\ddot{C}(SNR)}{\dot{C}(SNR)}+2+\frac{1}{2SNR}\int_{-1}^{+1}\frac{d\xi}{\tilde{S}_H(\xi)}\right)n_T f_D \\ &+ O(f_D^{3/2})\end{aligned} \tag{9}$$

where

$C(SNR) = \mathbb{E}[\log_2(1 + SNR|H|^2)]$

$\dot{C}(SNR) = \frac{1}{SNR}\left(\log_2 e - \frac{C(SNR)}{SNR}\right)$

$\ddot{C}(SNR) = \frac{1}{SNR^2}\left[\log_2 e + \dot{C}(SNR - 2\frac{C(SNR)}{SNR}\right]$

$\tilde{S}_H(\xi)$ is the doppler spectrum of the wireless channel.

f_D is the normalised doppler frequency

n_T is the number of transmit antennas

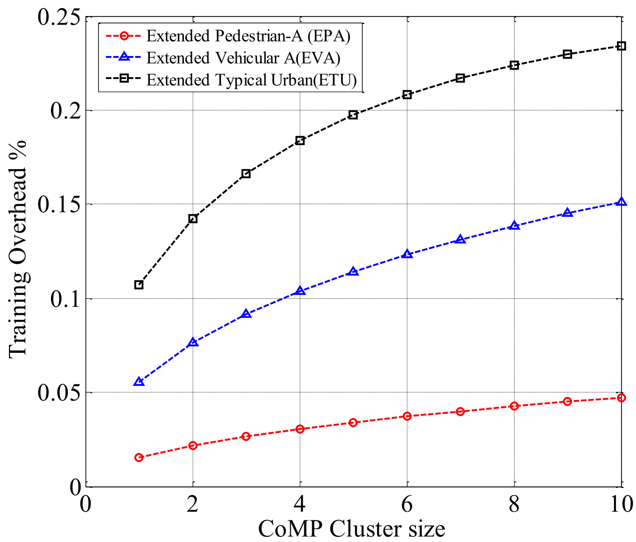


FIGURE 2. Optimum pilot overhead vs CoMP cluster size [23].

Figure 2 shows the optimum overhead required for three typical wireless channels widely used by 3GPP [24] for Clarke-Jakes spectrum with SNR=10dB. To estimate the pilot training overhead for any coalition C_i, we adapted the pilot requirement from (9) for extended pedestrian-a (EPA-A) case where: $f_D = 0.000357$ and the term $\int_{-1}^{+1}\frac{d\xi}{\tilde{S}_H(\xi)}$ simplifies to $\pi^2/2$ for Clarke-Jakes spectrum. We assume SNR=10 for training overhead estimation and one antenna for each SC, hence $n_T = |C_i|$.

Pilot overhead increases with cluster size $|C_i|$, and hence the actual bandwidth of a PRB for user data is reduced. This will then be reflected on the overall available capacity/load of all SCs within coalition C_i. Adjusted PRB bandwidth available for user data can be expressed as: $BW_{userdata} = BW_{total}(1 - \alpha)$

4) OTHER CHALLENGES

There are other challenges of CoMP implementation such as precoding, scheduling complexity and required backhaul bandwidth which increase as coalition size $|C_i|$ increases. To account for these additional costs, we define complexity factor $c(|C_i|)$. A soft maximum cluster size limit is imposed within the complexity factor where the cost of CoMP is sharply increased beyond a max coalition size limit $|C_i| > CS_{max}$. $|C_i|$ can still increase beyond CS_{max} in extreme conditions where the associated SE/load gain is higher than the increased cost. For any coalition C_i, complexity function is estimated as a sigmoidal function as follows:

$$c(|C_i|) = \frac{1}{1 + e^{-(|C_i| - CS_{max})}} \tag{10}$$

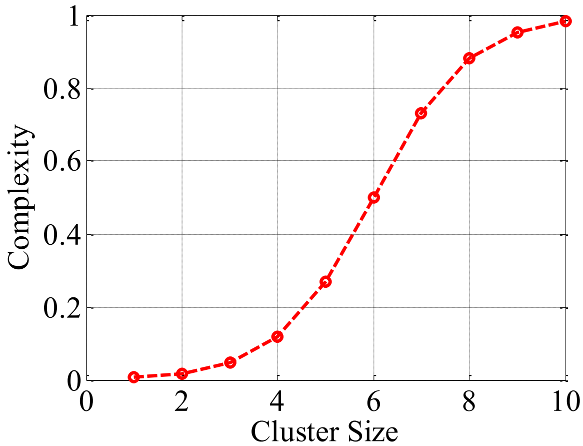


FIGURE 3. Complexity change with cluster size $|T_i|$, ($CS_{max} = 6$).

CS_{max} is designed to be an input parameter for the algorithm where it can be adjusted based on signal processing capacity and backhaul availability of the network. Figure 3 depicts the complexity factor used in our simulations when soft maximum cluster size is set to $CS_{max} = 6$.

IV. DYNAMIC NETWORK-CENTRIC CLUSTERING PROBLEM AS A COALITION GAME

Our goal is to find the best clustering structure $C = \{C_1, C_2, \ldots, C_s\}$ which best satisfies the network objectives in terms of CoMP performance and its overhead costs. Finding the best cluster formation by exhaustive search of every possible cluster combination is too complex especially when the network size is larger. As discussed in Section II, most of the existing solutions lack on scalability due to exponential increase in processing complexity as the network size increase. Applications of coalitional game theory in wireless networks is an emerging concept especially with CoMP and network coordination in general [25] to reduce this complexity. It provides a flexible analytical framework to provide distributed, low overhead, less complex solutions. We utilize coalition game theory and setup a coalition formation game to model the dynamic clustering problem for MU-JT CoMP in downlink and employ a utility function to optimize SE and LB jointly. We compare our solution with an improved version of a greedy clustering presented in [7]. We show that our solution outperforms the greedy solution and it provides a low complexity, scalable and stable clustering solution.

In this section, we first define the concepts for our coalition formation game model based on two simple transformation rules: merge and split. We then define two novel utility functions to employ in our coalition formation game. We discuss load-aware utility in detail and trade-off between performance improvement in LB/SE against the increased system complexity. We then present our novel network-centric clustering algorithm as a merge/split coalition game and discuss its complexity and stability properties.

A. COALITION FORMATION GAME CONCEPTS

Let $N = \{SC_1, SC_2, \ldots, SC_n\}$ be the players of the game, i.e. each player representing an SC in our scenario. Grand coalition is defined as the unique group of all cells in the game, i.e. N itself. Any cluster of SCs within the grand coalition is defined as a coalition $C_i = \{SC_{i1}, SC_{i2} \ldots SC_{iz}\}$. A collection is defined as a group of coalitions $C = \{C_1, C_2, \ldots, C_s\}$ and a collection is called a partition if all coalitions within C are disjoint coalitions i.e. $\forall i \neq j$, $C_i \cap C_j = \varnothing$ and all players (SCs) are included in one of the coalitions i.e. $\cup_{i=1}^{s} C_i = N$.

The utility (payoff) of a coalition C_i within the partition C is defined as $u(C_i, C)$ and the overall coalition game is uniquely defined by (N,u) pair. Utility of any coalition includes both the benefit and the cost for cooperation. Utility function for CoMP clusters in our scenario takes SE and cell load distribution into account as benefits and include a cost factor to account for increased computational complexity, pilot overhead and backhaul requirement with increased cluster size. The cost factor in the utility prevents a super-additive game, i.e. the cost increases with cluster size and hence it is mostly impossible to get all SCs to cooperate in a single cluster.

Characteristic form of a coalition game is defined such that the utility of any coalition $u(C_i)$ does not depend on how the rest of the partition $(N \backslash C_i)$ is structured i.e. $\forall i$ $u(C_i, C) = u(C_i)$. In our scenario, since we propose clustering changes in longer time intervals (seconds, minutes) where fast fading changes are averaged out as expressed in (6), the amount of interference created from the cells outside of the cluster are the same regardless of their clustering structure. Hence our scenario can be modelled as a coalition game in characteristic form. We make use of this property to reduce complexity of our algorithm as detailed in Section IV-D.

To compare the preference between 2 collections $C = \{C_1, C_2, \ldots, C_s\}$ and $H = \{H_1, H_2, \ldots, H_b\}$ of the same subset of players P where $P \subseteq N$, we define a comparison relation $\triangleright$, where $C \triangleright H$ means that coalitions in C is preferred to the coalitions in H. Various comparison orders are discussed in [26] but two orders are of notable importance for coalitional games for cooperative wireless networks [25]. First one is the utilitarian order which compares the utility of the overall collection. The players in P prefer to move to collection C from collection H i.e. $C \triangleright H$ if $\sum_{i=1}^{s} u(C_i) > \sum_{i=1}^{b} u(H_i)$, in other words, the total utility of all coalitions within collection C is greater than the one in collection H, irrespective of individual player utilities. The second important order is known as pareto order which compares the individual player utilities to make sure none of the players are worse off due to new collection formation and at least one player is better off. For a given subset of players P, the utility of player P_i in collection C is denoted as $u(P_i, C)$; then $C \triangleright H$ if $\forall i \in P$, $u(P_i, C) \geq u(P_i, H)$.

It's highly appealing to employ utilitarian order in our coalition game to maximize the overall system utility. The aim of our proposed coalition formation game is to maximize the total utility regardless of the utility for any individual SC. In other words, if the utility gain of a group of SCs is higher than the utility loss of the remaining SCs, then the corresponding clustering change shall be performed. In a typical hotspot scenario, cluster changes aim to reduce load for SCs with very high load (players with better payoff) but this will inevitably cause increased traffic in other SC where load is not as high (players with worse payoff). This clustering change is preferred in utilitarian order if the overall utility is increased however this is not allowed in pareto order as some players are worse off regardless of the overall utility.

To form coalitions and dynamically adapt the coalitions based on user profile/network changes, 2 simple transformation rules are followed:

- **Merge:** Players (SCs) in any two or more coalitions $\{C_1, C_2, \ldots, C_s\}$ prefer to merge into one coalition $F = \cup_{i=1}^{s} C_i$ i.e. $\cup_{i=1}^{s} C_i \triangleright \{C_1, C_2, \ldots, C_s\}$, if $u(F) > (\sum_{i=1}^{s} u(C_i))$ following the utiliterian order.
- **Split:** Players (SCs) prefer to split from any coalition C_i into smaller coalitions $\{C_{i1}, C_{i2}, \ldots, C_{iy}\}$ where $C_i = \cup_{j=1}^{y} C_{ij}$ i.e. $\{C_{i1}, C_{i2}, \ldots, C_{iy}\} \triangleright C_i$ if $(\sum_{j=1}^{y} u(C_{ij}) > u(C_i)$ following utiliterian order.

B. UTILITY FUNCTION

Utility function $u(SC_m, C_i)$ is defined to calculate payoff for any SC_m (player) in coalition C_i and payoff for any coalition $u(C_i)$ is simply the total payoff of all SCs within the coalition i.e. $u(C_i) = \sum_{SC_j \in C_i} u(SC_j, C_i)$. Utility function should reflect both the proposed performance improvement and the associated overhead costs of any coalition formation. Firstly, we define a load-aware utility function aiming to jointly maximize SE and LB objectives. The goal is to distribute SC load evenly and relieve congestion in hotspot scenarios while keeping SE at high levels and also provide high SE in non-hotspot scenarios when LB is not required. Secondly, we define an SE-based utility intending to maximize SE only for comparison to our load-aware utility.

1) **Load-aware utility:** For any SC_m in coalition C_i, load-based utility function is defined as follows:

$$u_1(SC_m, C_i) = \begin{cases} \dfrac{-(\hat{l}_{im})}{1 - c(|C_i|)}\hat{u}_{im} & \hat{l}_{im} < 1 \\ \dfrac{-(\hat{l}_{im})^3}{1 - c(|C_i|)}\hat{u}_{im} & \hat{l}_{im} \geq 1 \end{cases} \tag{11}$$

The main aim of the load-aware utility is to jointly optimise LB and SE by reducing SC load $\hat{l}_{im}$ which then implicitly enforces for better SE. When SE is improved, less radio resources are used for any given demand, and hence load is reduced. Payoff for each SC $u_1(SC_m, C_i)$ is reduced as SC load $\hat{l}_{im}$ increases. Once the cell is congested (i.e. $\hat{l}_{im} \geq 1$), any load increase is penalized more than the case when $\hat{l}_{im} < 1$. This is achieved by increasing the impact of load with the term $(\hat{l}_m)^3$ in the utility function in (11) when $\hat{l}_{im} \geq 1$. In other terms, additional payoff incentive is introduced for reducing the load in high load range, when compared to low load, i.e. enabling load distribution from congested SCs to lightly loaded SCs. In the high load range, distribution of load is given higher priority and hence clustering decisions in this range will prioritize LB improvement despite other clustering solutions may be available with better overall SE. In low-load range, $u_1(SC_m, C_i)$ will provide similar results to SE-based utility as SC load reduction implicitly enforces higher SE. Payoff $u_1(SC_m, C_i)$ is also directly proportional with "virtually dedicated" user count $\hat{u}_{im}$ i.e. highly loaded cells with more active users are given more incentive to reduce load and achieve better payoff. This promotes fairness in the system and aims to reduce the total number of unsatisfied users z_{im} at each SC. Term $c(|C_i|)$ in $u_1(SC_m, C_i)$ represents the complexity factor as the cluster size increases. Complexity function $c(|C_i|)$ enforces low cluster size $|C_i|$, by introducing high payoff penalty as the cluster size increases. Cluster size is only increased when the payoff incentive from reducing the load is higher than the payoff penalty introduced with $c(|C_i|)$.

Figure 4 illustrates the utility function $u_1(SC_m, C_i)$ against SC load $\hat{l}_{im}$ for different cluster sizes $|C_i|$ for $\hat{u}_{im}$=50 and $c(|C_i|) = \frac{1}{1+e^{-(|C_i|-CS_{max})}}$ when $CS_{max} = 6$. It can be seen that payoff only gradually increases as the load decrease in low load range, whereas there is sharper payoff increase in high load, in other terms, the load-aware utility provides additional payoff incentive to reduce load in high load range. On the other hand, increasing cluster size is penalized with complexity factor $c(|C_i|)$ where a sharp payoff penalty is observed especially moving from $|C_i| = 5$ to $|C_i| = 6$ in this example. A higher cluster size is expected in high load when compared the low load as the payoff incentive for reducing the load is higher in high load range as introduced in $c(|C_i|)$. A dynamic trade-off between cluster size/complexity and SE/load is formed with this utility where maximum cluster size limit is dynamically adjusted based on load situation in the network. The cost/gain factors and the trade-off between system complexity and LB/SE performance in $u_1(SC_m, C_i)$ provides a sample which can be adjusted based on specific radio network operator priorities. For example, in a highly customer-centric network, performance can be favored more than complexity in hotpots and to minimize the number of unsatisfied users due to congestion, term $\hat{l}_{im}^3$ when $\hat{l}_{im} \geq 1$ can be adjusted to give more incentive for reducing load in high load range. Similarly, $c(|C_i|)$ can be adjusted to increase maximum allowed cluster size in high/low load ranges. Our simulation results in Section V show the proposed dynamic cluster size adaptation depending the load situation, i.e. increasing cluster size dynamically when there is high load and hence improve SE/LB performance in both HN and RN scenarios.

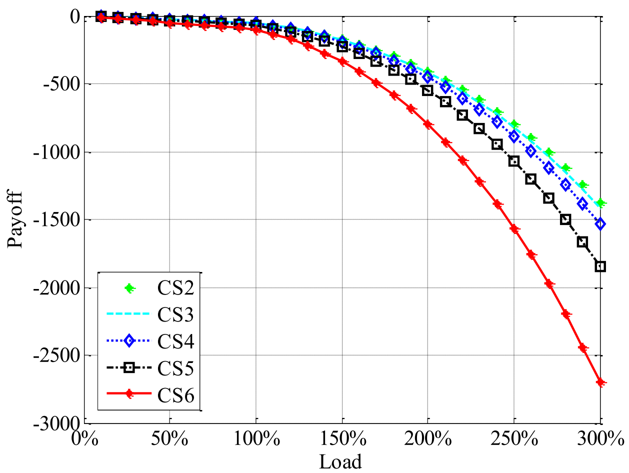


FIGURE 4. Utility function $u_1(SC_m, C_i)$ vs SC load $\hat{l}_m$ for different cluster sizes when $\hat{u}_m = 50$ and $CS_{max} = 6$.

2) **SE-based utility:** We define a second utility function to maximize SE, without considering load conditions. This utility is employed in our game model and in a greedy algorithm to compare with our load-aware utility.

SE-based utility function is introduced as follows:

$$u_2(SC_m, C_i) = \sum\nolimits_{k\in\hat{U}_{im}} y_k(1 - c(|C_i|)) \quad (12)$$

where:

$\hat{U}_{im}$ is the list of users where SC_m is the best serving cell based on average received signal power, i.e. a subset of the associated users U_{im} at the SC_m. y_k is the SE achieved at UE_k i.e. $y_k = log_2(1 + SI\hat{NR}_k^{aver})$.

The SE experienced at each user is added up to get the total utility at SC_m and complexity factor $c(|C_i|)$ is embedded to impose a soft cluster size limit similar to the one in load-aware utility in (11).

Similar to the two utility functions presented above, other utilities can be designed to optimize different network objectives like SE, load balancing, energy efficiency and backhaul availability etc. Furthermore, a combination of different network objectives can be embedded within the same utility function to jointly optimize multiple network objectives. Our novel clustering model based on merge/split coalitional game sets a flexible framework to employ various utility functions aiming for different network objectives.

C. MERGE/SPLIT OPERATION

Let $C = \{C_1, C_2, \ldots, C_s\}$ be a partition of N, i.e. the current status of the network. We propose to start merge operation with C_i which has got the maximum absolute payoff value. In both utility functions defined in (11) and (12), high absolute payoff value refers to coalitions with high number of active users and hence high load. Coalition C_i looks for neighbor coalitions C_j for any possible merge operation. We define neighbor coalition concept to avoid exhaustive search for merge operation and reduce complexity, i.e. merge operation will not be tried for every other coalition in the system but only towards the neighbor coalitions.

Neighbor definitions are performed by utilizing the average received reference signal level measurements received from the users. Firstly a simple neighbor relations list is performed at SC level. For any UE_k in the serving area of SC_m, the average received signal from all other SC_j where $P_{kj}^{rx} > P_{min}^{nei}$ are compared. A neighbor rank count is incremented for $\{SC_m, SC_j\}$ pair if $P_{kj}^{rx}/P_{km}^{rx} > P_{\Delta}^{nei}$. Once each SC has a rank based neighbor list, then neighbors at cluster level are calculated in a similar way i.e. the neighbor rank is incremented for $\{C_m, C_j\}$ coalition pair when $SC_m \subseteq C_m$, $SC_j \subseteq C_j$, $P_{kj}^{rx}/P_{km}^{rx} > P_{\Delta}^{nei}$ and $P_{kj}^{rx} > P_{min}^{nei}$.

The possibility of a merge operation is checked for all neighbor coalitions of coalition C_i and merge is performed with C_j if $u(C_i \cup C_j) > u(C_i) + u(C_j)$ based on utilitarian order as described in Section IV-A. Once a merge operation is successful, then neighbor lists are updated for the new merged coalition $(C_i \cup C_j)$ and further possible merges are searched in a similar fashion until there is no more neighbors left for a possible merge operation. Same process is repeated for the rest of the coalitions in partition $C = \{C_1, C_2, \ldots, C_s\}$ in absolute payoff value order as illustrated in Algorithm 1 until there is no more merges possible. A new partition H if formed at the end of the merge operation. Partition H is then subject to split operation where every coalition H_i is checked for all possible split options and it's split only when the total payoff of the split coalitions are better than the bigger coalition following utilitarian order i.e. $(\sum_{j=1}^{y} u(H_{ij}) > u(H_i)$. Split operation is successively iterated for the rest of the coalitions in partition H until no more split is possible as outlined in Algorithm 2. Merge and split operations are then performed iteratively until there is no more merge and split possible and the algorithm terminates. Termination of the algorithm is always guaranteed as all merge and split operations aim for the same objective i.e. increase the overall system utility $u(C)$. There is always a finite number of merge/split operations possible for increasing $u(C)$ and the algorithm will terminate when there is no room to increase $u(C)$ by merge/split operations.

D. ALGORITHM COMPLEXITY

Exhaustive search for any potential merge operation can increase complexity of the algorithm exponentially as the network size increase. Unlike exhaustive search proposed in previous network-centric clustering solutions like [7], [10], [10], we define neighbor cluster concept as described in section IV-C and propose merge operation only with neighbor clusters which reduces merge operation complexity and makes the algorithm scalable for larger networks.

Split operation can be a complex task as the number of possible splits increase exponentially with cluster size. To reduce this complexity, we utilize the characteristic form property of our coalition game where the possibility of any split operation does not depend on how the rest of the SCs are clustered.

Algorithm 1 Merge Operation

For any given network clustering state $C = \{C_1, C_2, \ldots, C_s\}$, $\forall C_i \in C$, set C_i.clustered $= 0$
Merge-ongoing $= 1$
while Merge-ongoing **do**
  Merge-ongoing $= 0$
  Sort $\forall C_i \in C$ based on $u(C_i)$ in descending order
  for all C_i where C_i.clustered $= 0$ **do**
    Update C_i.nei
    for all C_j in $C_i.nei$ where C_j.clustered $= 0$ **do**
      Update payoff gain for possible merge(C_i, C_j) i.e. $\delta_{u_{ij}} = u(C_i \cup C_j) - \{u(C_i) + u(C_j)\}$
    end for
    Find $C_m \in C_i.nei$ where $\delta_{u_{im}} = \max_{C_j \in C_i.nei} (\delta_{u_{ij}})$ and $\delta_{u_{im}} > 0$
    while C_m exist **do**
      Merge(C_i, C_m)
      C_m.clustered $= 1$
      Update C_i.nei
      for all C_j in $C_i.nei$ where $C_j.clustered$=0 **do**
        Update payoff gain for possible merge(C_i, C_j) i.e. $\delta_{u_{ij}} = u(C_i \cup C_j) - \{u(C_i) + u(C_j)\}$
      end for
      Find $C_m \in C_i.nei$ where $\delta_{u_{im}} = \max_{C_j \in C_i.nei} (\delta_{u_{ij}})$ and $\delta_{u_{im}} > 0$
    end while
    C_i.clustered $= 1$
    if Any merge operation with C_i **then**
      Break for-loop and continue with while-loop
      Merge-ongoing $= 1$
    end if
  end for
end while

Once we check a coalition for a possible split and if there is no possible split operation, then even when the rest of the network is re-clustered, marked coalitions will not be checked again for split in the following iterations.

Furthermore, in our coalitional game model, we have a soft maximum cluster size limit embedded in both utility functions to avoid increased signal processing and backhaul bandwidth required for CoMP. This limitation reduces the complexity on the split operation, i.e. less number of possible split options are available due to limited cluster size. Additionally, the split operation stops searching for other split options once a split option with better utility is found and hence the split operation does not have to go through all split options in most cases.

In summary, we define a low complexity merge and split operation in our novel game-theoretic clustering algorithm: We limit the merge operations to only neighbor clusters which improves scalability of the solution and reduces complexity. Additionally, a soft maximum cluster size limit is embedded in both utility functions which reduces complexity on split operation preventing high number of potential splits. Furthermore, we make use of the characteristic form property of our coalitional game model and reduce split complexity further. The stability of the algorithm and convergence to the best outcome is discussed in the next section.

Algorithm 2 Split Operation

For any given network clustering state $C = \{C_1, C_2, \ldots, C_s\}$, $\forall C_i \in C$, set C_i.splitpossible $= 1$

Split-ongoing $= 1$
while Split-ongoing **do**
  Split-ongoing $= 0$
  for all C_i where (C_i.split-possible $= 1$ and $|C_i| > 1$) **do**
    Update C_i.Split-options
    C_i.split-possible $= 0$
    for all C_i.Split-Options **do**
      if Any split option is possible i.e. $(\sum_{j=1}^{y} u(C_{ij}) > u(C_i)$ **then**
        Split(C_i to $\{C_{i1}, C_{i2}, \ldots, C_{iy}\}$
        Split-ongoing $= 1$
        $\forall C_{ij}$, set C_{ij}.split-possible $= 1$
        Break for-loop and continue with next C_i
      end if
    end for
  end for
end while

E. PARTITION STABILITY

We utilize a novel concept of defection function $\mathbb{D}$ introduced in [27] to analyze stability of our merge/split coalition game. Defection function $\mathbb{D}(C)$ of a partition C associates partition C with a set of collections. Partition C is defined as $\mathbb{D}$-stable if none of the players have any incentive to leave the partition to form collections allowed by $\mathbb{D}$.

The most robust stability is defined as $\mathbb{D}_c$ stable if it is the unique partition where the utility is maximum, i.e. there is no intention for any players to deviate into any other partition [27]. A partition $C = \{C_1, C_2, \ldots, C_s\}$ is $\mathbb{D}_c$ stable only if below 2 conditions are satisfied [27]:

1) $\forall C_i \in C$, any disjoint coalitions C_{ia} and C_{ib} in C_i where $C_{ia} \cup C_{ib} \subset C_i$, then $u(C_{ia} \cup C_{ib}) \geq u(C_{ia}) + u(C_{ib})$ i.e. any a sub-group of players in any coalition dont have any additional payoff incentive to leave the coalition.
2) For any arbitrary coalition A in N where $A \not\subset C_i$ and all players in coalition A may not belong to the same coalition in C, then: $\sum_{i=1}^{s} u(C_i \cap A) \geq u(A)$

$\mathbb{D}_c$ is the most desired form of stability as it is the unique partition with maximum utility, however partitions formed from merge/split game does not always guarantee $\mathbb{D}_c$ partitions. Our merge/split coalition game results in the $\mathbb{D}_c$ stable partition depending on the network and user profiles. In a typical SC deployment scenario, basic coverage is provided by the MBS, and SCs are deployed in hotspot areas only. There are hotspot areas within the MBS coverage area where

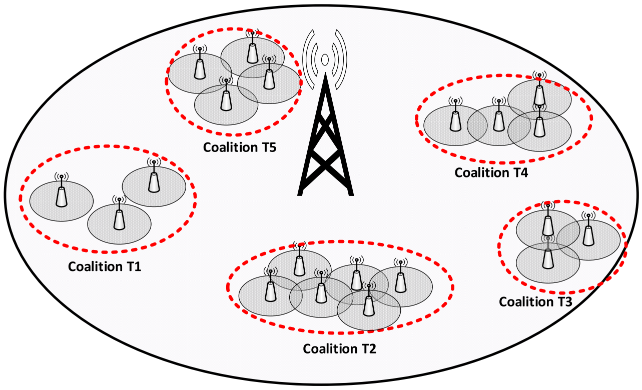


FIGURE 5. An illustration of $\mathbb{D}_c$ stable partitions.

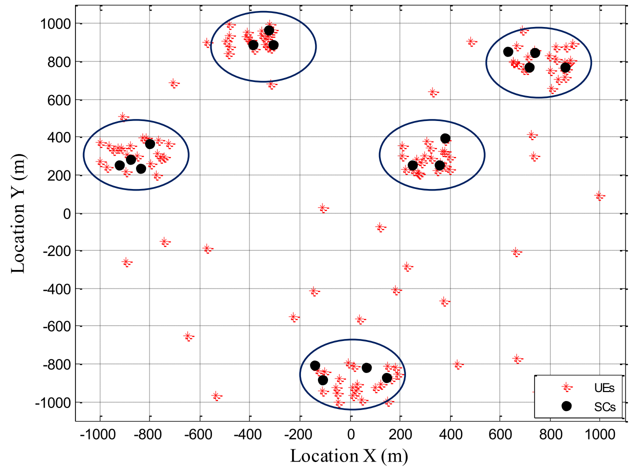


FIGURE 6. $\mathbb{D}_c$ stable partitions from merge/split cluster formation game.

most users and SCs are concentrated as illustrated in Figure 5. We show that both conditions of $\mathbb{D}_c$ stability are guaranteed in this deployment scenario as follows:

Condition 1 for a $\mathbb{D}_c$-stable partition C states that for each coalition $C_i \in C$, any 2 disjoint sub-coalitions $C_{ia}, C_{ib} \in C_i$ won't have additional payoff to form separate coalitions. In our model, there is dense deployment of SCs and high concentration of users in small hotspot areas where inter-cell interference is high due to dense deployment in the absence of CoMP. Therefore, there is high payoff incentive to form C_i to include all SCs within the same hotspot area in both utility functions in (11) and (12) as severe inter-cell interference is mitigated, improving SE (y_k in (12)) and hence reducing the cell load $\hat{l}_m$ in (11). The cost ($c(|C_i|)$) of forming this coalition is kept low when $|C_i| < CS_{max}$ and it increases exponentially when the coalition size increase beyond CS_{max}. Therefore, our coalition game forms the coalitions to include all SCs within the same hotspot when the number of SCs within the same hotspot do not exceed CS_{max}.

Let C_i be the coalition including all SCs within any hotspot location where $|C_i| < CS_{max}$, and assume C_{ia} and C_{ib} are 2 disjoint sub-coalitions of coalition C_i. Individual SCs in C_i will not have better payoff for leaving C_i to form a smaller sub-cluster C_{ia} i.e. $\forall SC_m \in C_i$, $u(SC_m, C_i) > u(SC_m, C_{ia})$. SCs will have better payoff in bigger clusters due to improved inter-cell interference mitigation provided that the size of the bigger cluster does not exceed CS_{max}, i.e. for any 2 disjoint sub-clusters, $\forall SC_m \in C_{ia}, u(SC_m, (C_{ia} \cup C_{ib})) > u(SC_m, C_{ia})$, and thus $u(C_{ia} \cup C_{ib}) > u(C_{ia}) + u(C_{ib})$. Condition 1 for $\mathbb{D}_c$ stability is satisfied when $|C_i| < CS_{max}$.

For a $\mathbb{D}_c$-stable partition C, condition 2 states that any players from different coalitions C_i and C_j have no additional payoff to form another coalition H_i where $H_i \notin C$. Let C_i and C_j be the coalitions of SCs in two separate hotspots and $|C_i| < CS_{max}$ and $|C_j| < CS_{max}$ so condition 1 of a $\mathbb{D}_c$ stability is satisfied i.e. all SCs within the same hotspot are in the same coalition with no incentive to leave and form smaller coalitions. There is no incentive for any $SC_i \in C_i$ and $SC_j \in C_j$ to form another coalition if the distance between the two are $> d_0$ where no user UE_k have any incentive to have both SC_i and SC_j in the same user-centric cluster C_i^k. This is guaranteed when for any UE_k, if the average received signal power from SC_i from distance d_{ki} is above the minimum threshold for clustering i.e. $P_{ki}^{rx}(d_{ki}) > P_{min}$, then $P_{kj}^{rx}(d_{kj})$ should be below P_{min}. Similarly, if $P_{kj}^{rx}(d_{kj}) > P_{min}$, then $P_{ki}^{rx}(d_{ki}) < P_{min}$. Assuming distance based path loss only for simplification, to satisfy this condition for any UE_k, the worst case scenario is considered where UE_k is located in the middle of SC_i and SC_j with equal distance. If the distance between SC_i and SC_j is $> d_0$ where both $P_{ki}^{rx}(d_0/2) < P_{min}$ and $P_{kj}^{rx}(d_0/2) < P_{min}$ then it is guaranteed that SC_i and SC_j can never be in the same user-centric cluster C_i^k i.e. average received power will not be above P_{min} for both SCs for any arbitrary user, hence there is no incentive for SC_i to leave C_i to form a new coalition with SC_j from coalition C_j, i.e. condition 2 is satisfied.

In summary, our merge/split formation game results in a $\mathbb{D}_c$ stable partition in our typical deployment scenario where merge/split operation results in forming coalitions including all SCs within the local hotspot areas if the number of SCs within the same hotspot is not higher than the maximum cluster size limit and the distance between the hotspot areas are $> d_0$. Figure 6 shows the clustering results from our merge/split cluster formation game in a typical SC deployment scenario in hotspots. Unique $\mathbb{D}_c$ stable partition is achieved in this deployment scenario where all local SCs within the same hotspot are included in the same cluster.

In the case when the SC deployment is not so dense, or low power SCs are used with almost isolated coverage areas, i.e. there is very limited inter-cell interference, proposed solution will not form clusters around all cells within hotspot as there won't be enough payoff incentive to justify cluster formation. This intuitively implies that expected CoMP gain would be minimal in this scenerio, and there won't be a unique $\mathbb{D}_c$ stable partition around all SCs within the same hotspot area. In other sceneries, where there is no specific hotspot deployment, or the number of cells within hotspot area exceed CS_{max}, unique $\mathbb{D}_c$ stable partition will not exist. In these cases, a more relaxed defection function $\mathbb{D}_{hp}$ is defined in [27] where for any partition C, players are allowed leave to form another partition only by means of possible merge and splits. As our coalition game only follows merge/split operations and always terminates as there is only finite number of merge/split possible which can increase the overall system utility, all partitions resulting from our merge/split coalition game are always $\mathbb{D}_{hp}$ stable. $\mathbb{D}_{hp}$ stability does not have to be unique and other partitions with better utility may exist. To improve the merge/split game clustering outcome when $\mathbb{D}_c$ stability is not possible, we propose to start merge operations from the coalition with the maximum absolute payoff value aiming to achieve better utility for the loaded cells and maximize the resulting partition utility.

In summary, $\mathbb{D}_c$ stability provides the most desired unique partition with maximum utility and this is achievable in our merge/split game in certain network conditions which is most likely to be the deployment scenario for future networks. In the case when $\mathbb{D}_c$ stability is not possible, all partitions from our merge/split game are $\mathbb{D}_{hp}$ stable.

V. SIMULATION RESULTS

To evaluate the performance of the proposed load-aware, game-theoretic clustering framework, simulations are run for both HN and RN scenarios with various hotspot schemes. To compare our load-aware clustering model performance based on load-based utility in (11), we employed SE-based utility in (12) as well in our framework and additionally we compared simulation results with an improved version of the greedy algorithm proposed in [7]. We adapted our novel SE-based utility function (12) in the greedy algorithm and lifted the maximum cluster size limit in [7] as the cluster size is self-limited with cost function $c(|C_i|)$ within the utility function in (12). We also reduced complexity of the algorithm in [7] and utilized our neighbor coalition concept where only neighbor coalitions are considered for possible clustering as described in Section IV-D. Greedy algorithm starts with a random SC and forms clusters with neighbor SCs starting from the SC with maximum joint payoff. Unlike merge/split game clusters, greedy clusters lack on additional split functionality and also the randomness of the starting SC can provide under-optimized clustering solution depending on which SC the algorithm starts with. Algorithm 3 shows a summary of the enhanced version of the greedy algorithm presented in [7].

Following abbreviation is used in the rest of this section:
SE-GR: Greedy clustering with SE-based utility.
SE-GA: Game-theoretic clustering with SE-based utility.
L-GA: Game-theoretic clustering with load-based utility.

A network of SCs within one MBS is considered for our simulations as described in Section III. Each SC is assumed to have one cell with omni directional antenna for simplicity. ITU-R microcell urban non-line-of-sight (NLOS) path loss

Algorithm 3 Greedy Clustering

> Initiate Clusters i.e. $\forall C_i \in C$, $C_i = \{SC_i\}$ and C_i.clustered $= 0$
> **for all** C_i where C_i.clustered $= 0$ **do**
>   Update C_i.nei
>   **for all** C_j in $C_i.nei$ where C_j.clustered $= 0$ **do**
>   Update payoff gain for possible merge(C_i, C_j) i.e. $\delta_{u_{ij}} = u(C_i \cup C_j) - \{u(C_i) + u(C_j)\}$
>   **end for**
>   Find $C_m \in C_i.nei$ where $\delta_{u_{im}} = \max_{C_j \in C_i.nei}(\delta_{u_{ij}})$ and $\delta_{u_{im}} > 0$
>   **while** C_m exist **do**
>   Merge(C_i, C_m)
> C_m.clustered $= 1$
>   Update C_i.nei
>   **for all** C_j in $C_i.nei$ where $C_j.clustered = 0$ **do**
>   Update payoff gain for possible merge(C_i, C_j) i.e. $\delta_{u_{ij}} = u(C_i \cup C_j) - \{u(C_i) + u(C_j)\}$
>   **end for**
>   Find $C_m \in C_i.nei$ where $\delta_{u_{im}} = \max_{C_j \in C_i.nei}(\delta_{u_{ij}})$ and $\delta_{u_{im}} > 0$
>   **end while**
> C_i.clustered $= 1$
> **end for**

model in [28] is adapted in our simulation as given in (13).

$$PL = 36.7\log_{10}(d) + 22.7 + 26\log_{10}(fc) \tag{13}$$

TABLE 1. Simulation parameters.

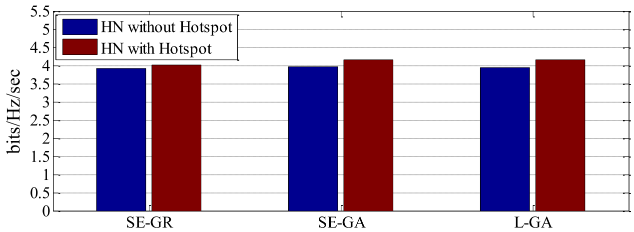
Parameter Name	Parameter Value
Simulation Enviroment	Urban Microcell [28]
Frequency Carrier	5 Ghz
Channel Bandwidth	5 Mhz
RB Bandwidth	180kHz
Number of PRBs/SC	25
Shadow fading std	4 dB [28]
UE Antenna Gain	0 dBi
UE Thermal Noise Density	-174 dBm/Hz
TP Total Transmit Power	41dBm [28]
UE Noise Figure	7dB
TP Noise Figure (inc cable loss)	5dB
SC antenna gain (boresight)	17dBi
User-centric cluster: Min RX Power (P_{min})	-110dBm
User-centric cluster: Max RX power offset (P_{Δ})	20dB
Min RX power for Neighbor Def. (P^{nei}_{min})	-110dBm
Max RX power offset for Neighbor Def. (P^{nei}_{Δ})	-6dB
GBR for UEs in the hotspot in RN Scenario	512 kbps
GBR for UEs outside the Hotspot in RN Scenario	256 kbps
GBR for UEs in HN Scenario	512 kbps
SC Density for RN (λ_N)	80SC/km^2
UE Density within Hotspot in RN Scenario($\lambda_{K_{high}}$)	4000UE/km^2
UE Density outside Hotspot in RN Scenario($\lambda_{K_{low}}$)	200UE/km^2
RN Simulation Area Radius R_B	0.5km
RN SC deployment Area Radius	0.4km
RN Hotspot Area Radius	0.1km

Rest of the simulation parameters are summarized in Table 1. We ran our simulation 100 times for each deployment scenario described below and present the results from the average of 100 snapshots.

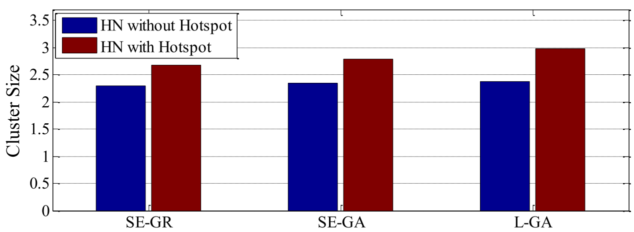
A. HOMOGENEOUS NETWORK (HN) SCENARIO

Firstly, we evaluate the performance for a HN deployment scenario where 25 SCs are located within the simulation area of 0.5kmx0.5km with 100m inter-site distance. 2 scenarios are evaluated in HN deployment:

- HN without hotspot: 250 UEs are distributed within the simulation area following uniform random distribution. A fixed GBR of 512kbps is assigned to each UE.
- HN with hotspot: 2 hotspot areas are assumed within the simulation area, each hotspot is 100mx100m with 125 UEs distributed in each hotspot area following uniform random distribution. 250 additional UEs are uniformly distributed in the whole test area including the hotspot areas. All UEs have a fixed GBR requirement of 512kbps.



(a) Average spectral efficiency in HN with/without hotspot.



(b) Average cluster size in HN with/without hotspot.

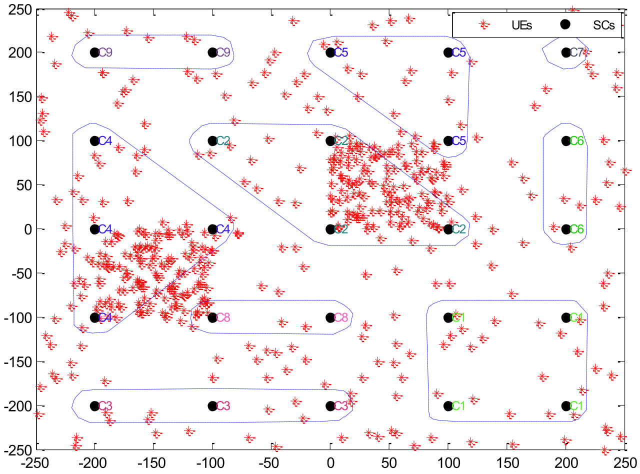
FIGURE 7. Average spectral efficiency and cluster size in HN with/without hotspot scenarios.

Figure 7a depicts the average SE and in HN with/without hotspot scenario for each of the clustering algorithms i.e. SE-GR, SE-GA and L-GA respectively. Without the hotspots, we observe similar SE improvement on SE-GR and SE-GA algorithms. This is an expected outcome as possible merge-split iterations in the coalitional game model does not play an important role when compared to greedy algorithm in forming clusters due to even distribution of SCs and users. We also observe that L-GA algorithm also achieve similar SE when compared to SE-GR/SE-GA, even though the employed utility function does not directly aim to maximize SE. Load-aware utility in L-GA aim to reduce load and improve load distribution which improves the SE indirectly. Average cluster size for each of the algorithm in HN without hotspot scenario is also similar as depicted in Figure 7b. CS is controlled by the same cost function $c(|C_i|)$ in both employed utility functions in (12) and (11), and hence similar average CS is expected for all 3 schemes in HN without hotspot scenario. It can be concluded that our novel load-aware clustering model (L-GA) perform as good as SE-based algorithm in maximizing SE when there is no over-load conditions.

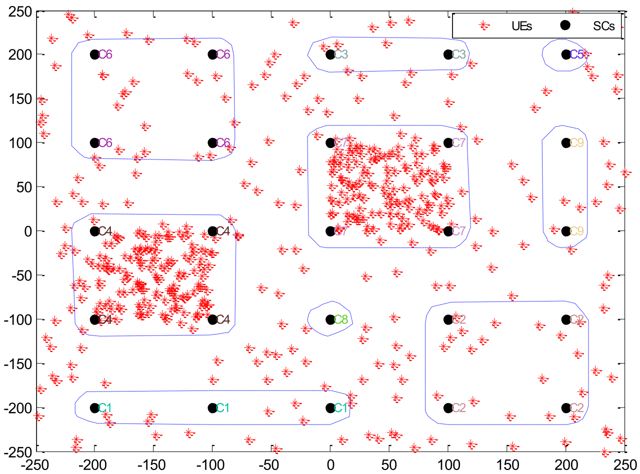
A more realistic network scenario is when the users are not uniformly distributed and there are hotspots at certain locations. Clustering is more challenging in this scenario where any clustering combination without load awareness can potentially reduce achievable performance. Figure 8 shows a snapshot of clusters formed from SE-GR, SE-GA and L-GA clusters respectively in HN with hotspot scenario. Due to random selection of SCs for clustering, greedy algorithm (SE-GR) fails to get SCs within the same hotspot in the same cluster in this snapshot. However, SE-GA cluster starts the clustering process from the SC/cluster with maximum absolute payoff value and hence SC/clusters with higher load are given the priority on forming the clusters. SE-GA clusters manage to form clusters including the nearest SCs to the hotspots which then improves the SE for majority of the UEs. L-GA clusters form larger clusters around the hotspots when compared to SE-GA and SE-GR. This is due to employed load-aware utility (11) providing more payoff incentive for reducing load in high load conditions overcoming the cost of increasing cluster size $c(|C_i|)$, resulting in bigger cluster size, improved inter-cell interference mitigation, better SE and hence reduced load with the expense of increased processing complexity and backhaul requirement.

SC load distribution in HN with hotspot scenario is depicted in Figure 9 where it is visible that highly loaded SCs are significantly reduced in L-GA clusters when compared to SE-GR/SE-GA clusters resulting in better load distribution. Consequently, a significant reduction in unsatisfied UEs is achieved in L-GA clusters when compared to SE-GR/SE-GA clusters as shown in Figure 10. Total number of unsatisfied users is reduced by 34.7% in L-GA when compared to SE-GR. A total of 12.95% of the UEs are unsatisfied in L-GA clusters whereas 19.85% and 18.18% of the UEs are unsatisfied in SE-GR and SE-GA clusters respectively. As depicted in Figure 7b, average cluster size is increased in SE-GA and L-GA models by 4.1% and 11.6% respectively when compared to SE-GR algorithm. Load-aware utility function (11) in L-GA provides additional payoff incentive for reducing load at highly loaded cells which can overcome the cost of increased cluster size resulting in higher cluster size in hotspot scenario and hence the L-GA model responds to hotspots much better than SE-GR and SE-GA.

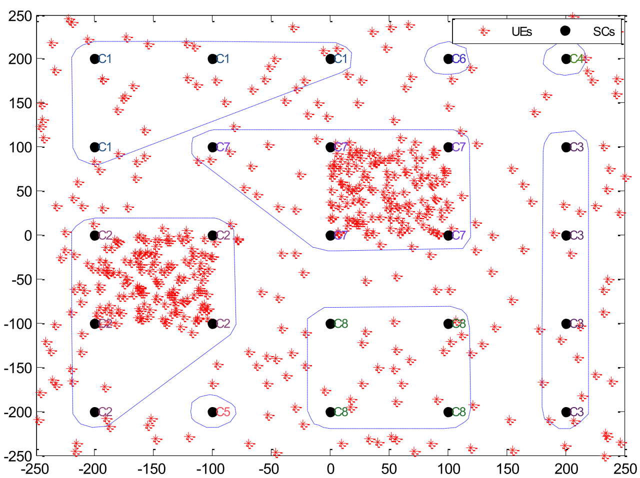
Our SE-based game theoretic clustering algorithm SE-GA also outperforms the greedy clustering SE-GR in hotspot scenario, where a marginal improvement in SE is observed, resulting from the fact that SE-GR algorithm starts from any random cell for clustering, resulting in non-optimum clustering solutions especially in hotspot scenario. Moreover, SE-GR algorithm lacks on iterative improvements introduced in merge/split game when compared to SE-GA and L-GA algorithms.



(a) SE-GR Clusters in HN with hotspots.



(b) SE-GA Clusters in HN with hotspots.



(c) L-GA Clusters in HN with hotspots.

FIGURE 8. Snapshot of SE-GR, SE-GA and L-GA clusters in HN with hotspot scenario.

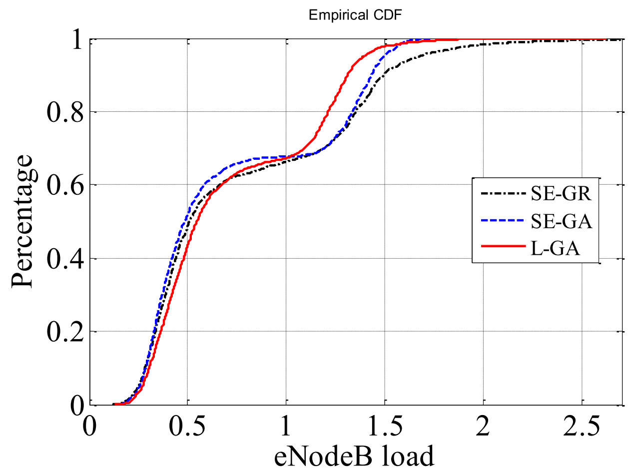


FIGURE 9. eNodeB load CDF in HN with hotspot.

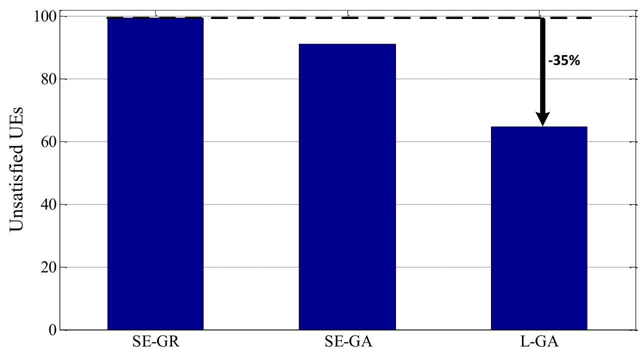


FIGURE 10. Unsatisfied UEs in HN with hotspot.

In summary, we show that our novel L-GA clusters result in significantly less number of unsatisfied UEs by distributing load more evenly while keeping SE at comparable levels in hotspot scenario. In non-hotspot scenario, L-GA clustering performs as good as SE-based approaches (SE-GR/SE-GA). Overall, L-GA model performs well in all scenarios with/without hotspots providing a multi-objective clustering model which jointly optimises cell load and SE. It is also shown that L-GA provides an interesting dynamic cluster size metric, where average cluster size is increased in hotspot conditions and it's reduced to lower levels when hotspot disappears in the network, providing a control on the additional complexity associated with increased cluster size. Moreover, we also show that our SE-based game theoretic clustering model (SE-GA) clusters result in better SE than greedy algorithm (SE-GR) in HN with hotspot scenario, due to cluster formation priority given to cells in hotspots first, and also the iterative process of merge/split algorithm outperforming greedy cluster formation.

B. RANDOM NETWORK (RN) SCENARIO

We evaluate our novel clustering solution further for a random network (RN) topology where SCs are randomly distributed within a circle of 0.4km radius following poisson point process (PPP) distribution with density parameter λ_N. All SCs within the circle are assumed to be connected to one MBS as described in Section III. UEs are also randomly distributed

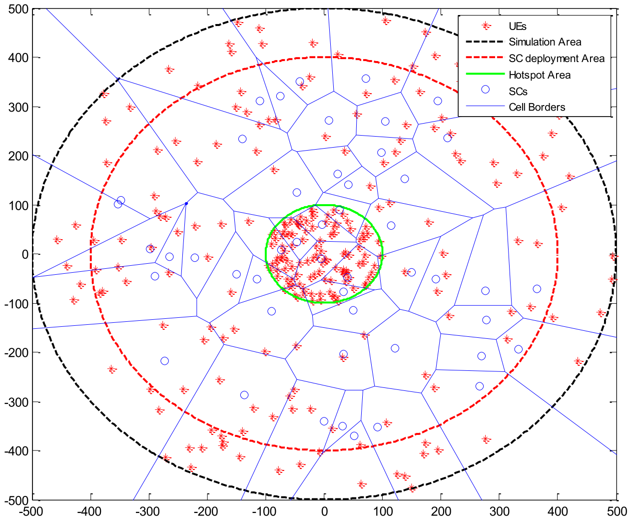
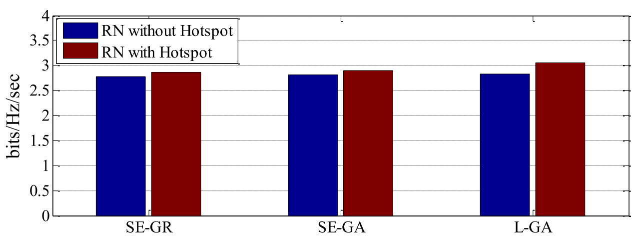
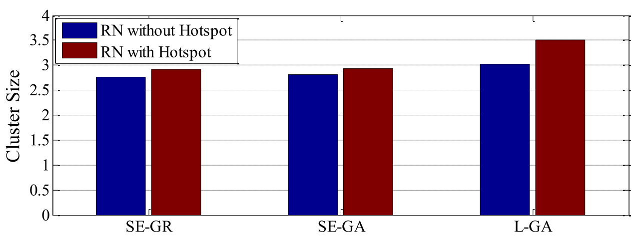


FIGURE 11. Random network simulation setup.

following PPP distribution. To simulate the hotspot scenario, higher user density is assumed within an inner circle with 0.1km radius with user density $\lambda_{K_{high}}$ and a low user density of $\lambda_{K_{low}}$ is simulated in the outer ring. Outer ring is assumed to go beyond SC deployment radius to make sure users are distributed in the whole coverage area of all SCs. In the non-hotspot scenario, both inner and outer circle user density has been set to the same lower density. A snapshot of the simulated network topology with hotspot is illustrated in Figure 11. Simulations are run for 100 times for each RN scenario and various user/UE distribution is generated at each snapshot following PPP distribution with same user/SC density.



(a) Average spectral efficiency in RN with/without hotspot.



(b) Average cluster size in RN with/without hotspot.

FIGURE 12. Average spectral efficiency and cluster size in RN with/without hotspot scenarios.

Figure 12a shows the average achieved SE for all clustering types for hotspot and non-hotspot scenarios. Similar to HN scenario, average SE is comparable on all 3 clustering types in evenly distributed traffic scenario where there is no hotspots, i.e. L-GA clusters perform as good as SE based clusters when there is no overload. In hotspot scenario, SE-based coalitional game model (SE-GA) achieves a 1.57% better SE than the greedy model (SE-GR), similar to HN results.

Our novel L-GA model achieves significant improvement in LB while keeping SE at high levels in hotspot scenario, resulting in reduced number of unsatisfied users. Average achieved SE is increased in L-GA model by 6.73% when compared to SE-GR as depicted in figure 12a. Figure 13 shows the load distribution of the SCs where L-GA clustering achieves significantly better load distribution with reduced amount of SCs in high load range when compared to SE-GR and SE-GA clusters. Figure 14 shows the average total number of unsatisfied UEs for each clustering algorithm in RN with hotspot. L-GA algorithm is significantly more effective in distributing the load and reducing the number of unsatisfied users, resulting in 68.50% less unsatisfied users when compared to SE-GR clusters. 3.63% of the UEs are unsatisfied in L-GA when compared to 11.54% and 12.14% in SE-GR and SE-GA respectively.

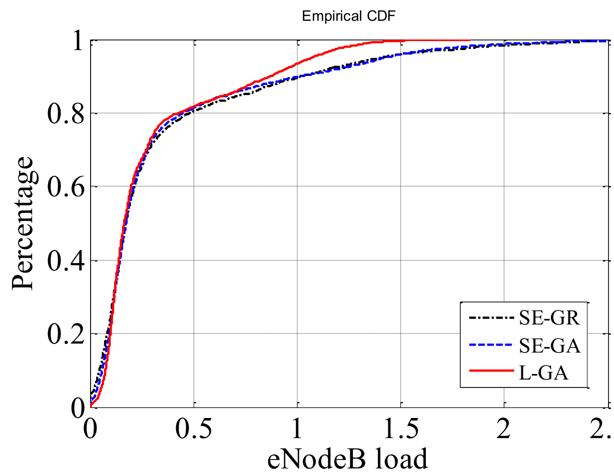


FIGURE 13. eNodeB load CDF in RN with hotspot.

Figure 12b depicts the average cluster size achieved for each clustering algorithm with and without hotspot scenario. Similar to HN results, average cluster size is increased in L-GA clusters significantly more than SE-GR and SE-GA clusters in hotspot scenario when compared to non-hotspot scenario due to additional payoff incentive in L-GA utility function to reduce load in hotspots. L-GA clusters manage to increase the cluster size in a self-organized way when there is high capacity requirement in hotspot scenario. Cluster size is dynamically reduced when the hotspot disappears and load is evenly distributed.

We further analyze merge/split iterations in RN scenario with and without the hotspots. In Figure 15, total payoff of all SCs is shown for each merge/split operation until the final cluster is formed for L-GA clusters in RN scenario with/without hotspot. At each merge/split operation, utilitarian order is followed where merge/split operation is only

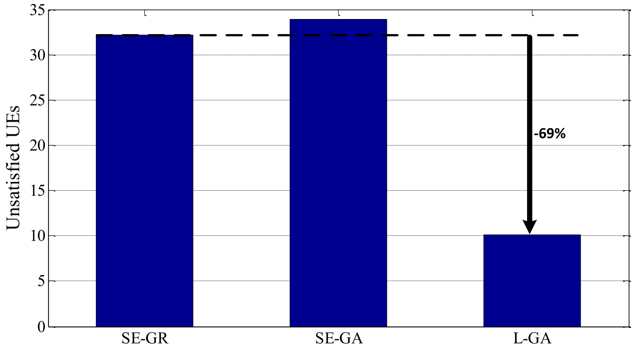


FIGURE 14. Unsatisfied UEs in RN with hotspot.

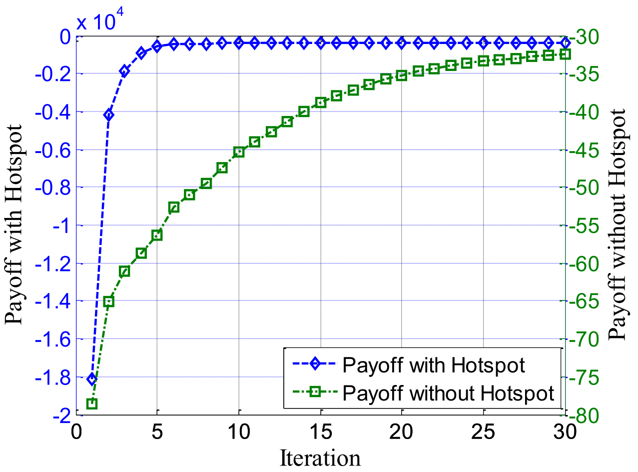


FIGURE 15. Payoff changes with merge/split iterations for L-GA algorithm in RN with/without hotspot scenario.

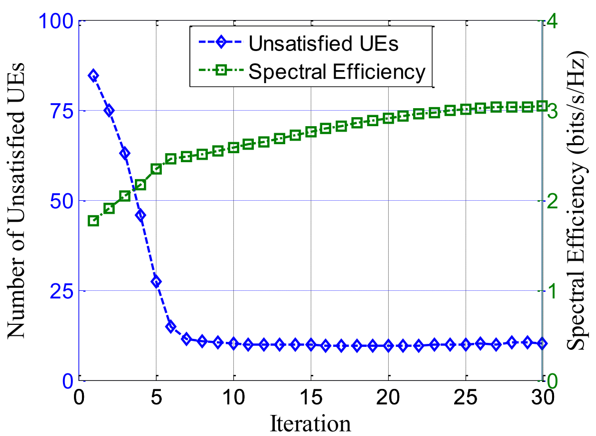


FIGURE 16. Unsatisfied UEs/spectral efficiency changes with split/merge iterations for L-GA algorithm in RN with hotspot scenario.

allowed if the total system payoff is increased. In hotspot scenario, payoff is sharply increased in the first few merge/split operation where highly loaded cells are clustered, resulting in lower SC load and a higher payoff. Payoff increase is more gradual in non-hotpot scenario where merge/split operation gives an average payoff for each cell as they are almost equally loaded. Figure 16 depicts the changes in unsatisfied UEs and SE for each merge/split iteration for L-GA algorithm in RN with hotspot scenario where our load-based utility function manages to improve both load and SE at the same time for each merge/split operation for majority of merge/split operations. Marginal reduction in SE is observed in later iterations for forming clusters to distribute load more evenly and therefore reduce unsatisfied UEs further with the expense of marginal SE reduction.

VI. CONCLUSION

In this paper, we propose a novel, load-aware network-centric clustering solution based on merge/split coalition game for CoMP deployment in future networks. We introduce merge/split coalitional game concepts and provide analysis on its stability and complexity. We show that our novel algorithm provides the unique partition with maximum utility when it is available, i.e. in the expected SC deployment scenario where SCs are deployed in local hotspot areas. In the case when this is not achievable, a more relaxed stability is always guaranteed where proposed algorithm converges to a final partition with no more merge/splits possible. Proposed solution is employed with two utility functions: SE-based utility is designed to maximize SE and load-aware utility aims to jointly optimize SE and LB objectives. It is shown that our SE-based clustering outperforms greedy algorithm providing better SE in scenarios where users are unevenly distributed. Furthermore, we show that our load-aware clustering model (L-GA) achieve significantly better load distribution while keeping SE at high levels. Unsatisfied UEs are reduced by 68.5% in RN scenario with hotspots in L-GA algorithm when compared to greedy clustering model. Moreover, L-GA model provides a self-organized cluster size metric where CS is increased in hotspot scenarios to reduce high load with the expense of higher processing complexity and backhaul requirement, and it is reduced back down when hotspot disappears. In summary, our novel load-based game theoretical clustering algorithm (L-GA) is shown to be low-complexity, stable clustering solution combining both SE and LB objectives into the same utility function which can dynamically adapt to both hotspot and non-hotspot scenarios.

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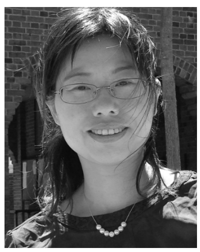

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