

Two-Step Matching Game for Minimizing Hand-off Failure Risk in Heterogeneous Networks

Alireza Shams Shafiqh and Savo Glisic

Centre for Wireless Communications, University of Oulu, Finland

Email: firstname.lastname@oulu.fi

Abstract—Small cell base stations deployment is a promising approach to offload traffic from macrocell, and improve the network capacity and coverage. However, interference management and providing seamless hand offs between access points (APs) for user equipments (UEs) remain main technical challenges especially in dense heterogeneous wireless networks. In this paper, a novel context-aware resource allocation (CARE) mechanism is proposed based on an adaptive space-time beamforming (ASTB) scheme, where different beam-widths (in time and space domains) are allocated to UEs according to their performance preferences with respect to delay tolerance, throughput, energy consumption and link robustness to the potential hand-off failure. We formulate CARE as a two-step matching game consisting of two many-to-one sub-matching games with externality for access and backhaul networks. We introduce two-step stable matching and Nash stability concepts as solutions of CARE. Our numerical results show that CARE with space-time beamforming provides at least two times higher capacity for UEs in comparison to space beamforming while the average delay and complexity are significantly decreased.

Keywords. Hand-off failure risk, many-to-one matching game, two-step Nash stability.

I. INTRODUCTION

The mixture of wired and wireless connectivity through small cells provided by users and operators will transform the way of accessing the Internet [1] in the future 5G networks. This heterogeneous connectivity provides a high level ubiquitous broadband access for network users with different preferences [2], [3], [4] and [5]. Associating a UE with a particular base station (BS) significantly affects such heterogeneous network performance [6]. Deploying dense small cell is a straightforward and effective approach to increase the network capacity (reduce the interference) by bringing BSs (APs) closer to users [6]. Unfortunately this reduces link robustness of the connections to hand off failures for fast moving vehicles. In general, an intuitive solution to minimize the number of hand offs for a fast moving terminal would be to connect to macro base station with increased beamwidth. On the other hand in such a case a few high-speed users could occupy the whole available spatial resources. In [7], the authors shows that there exists a fundamental trade off in the design of beamwidth: the wider beams in the space domain suffers from insufficient power while narrower beams are more sensitive to position estimation error.

In this paper, we develop a promising context-aware resource allocation (CARE) method based on a novel adaptive space-time beamforming (ASTB) scheme. Such CARE algorithm is able to serve UEs with different preferences with respect to link robustness to hand offs, delay tolerance, power consumption and throughput by deploying matching theory [8], [9], [10], [11]. In summary, contributions of this paper include proposals for:

- Developing CARE as a distributed context-aware resource allocation approach based on an adaptive space-time beamforming (ASTB) scheme.
- A two-step matching game model for CARE with two-step stable matching and Nash equilibrium as solutions.
- A coalition game model for further improving CARE algorithm by finding a Nash stable coalition through different time slots (referred to as CARE+).

The rest of the paper is organized as follows: Section II provides the general system model. UEs' and BSs' preferences in the form of their utilities are explained in Section III. The proposed CARE algorithm is described in Section IV and Section V develops Stable matching and Nash stability concepts as the solutions of CARE method. Section VI includes analysis and numerical results. Finally, Section VII concludes the paper.

II. SYSTEM MODEL

We consider a heterogeneous wireless network, shown in Fig.1, consisting of M macro cell base stations (macro eNBs or MBSs), A access points (APs), R relays and I UEs randomly distributed within the network. In the sequel \mathcal{M} , \mathcal{A} , \mathcal{R} and \mathcal{I} represent the sets of MBSs, APs, relays and UEs respectively. Notice that both APs and relays are referred to as small cell BSs (SCBSs) with different capabilities. APs have wired connections to the core network while relays connect to APs via wireless links. In the proposed scenario, \mathcal{SC} is the set of available sub-carriers. The proposed context-aware resource allocation (CARE) method jointly associates UEs to BSs and relays to BSs in the access and backhaul networks respectively.

Here mobile UEs prefer to be served by MBS in order to have the most robust communication link with minimum number of hand offs while the static UEs prefer the nearest BSs in order to acquire the highest data rate. In general, delay-sensitive UEs like to avoid the overloaded BSs. The link robustness is quantified by how long a link can be used by

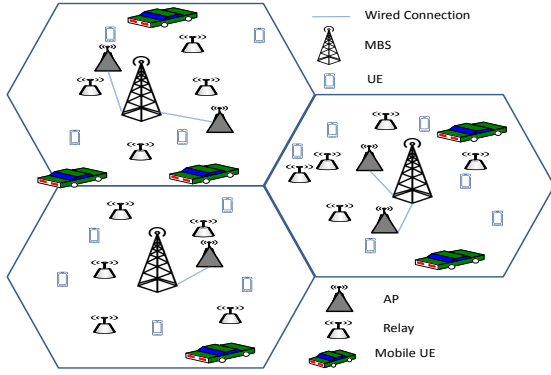


Fig. 1. System model with wired/wireless backhauls.

mobile UEs until link fails [12], [13]. The proposed CARE method uses an adaptive space-time beamforming (ASTB) scheme, shown in Fig.2, to meet the UEs' requirements. In this model, every BS spatially splits its beamwidth into ζ smaller sub-beams to increase spectrum reuse factor and antenna gain as well. In the example, shown in Fig.2, there are five different UEs sharing 360° beamwidth of BS j . The 360° beamwidth of BS j is divided into 8 sub-beams to provide different coverage areas for UEs according to their requirements. The width of each smaller sub-beam is $\theta = \frac{2\pi}{8} = \frac{\pi}{4}$. Every UE i needs at least one sub-beam to be able to communicate with the BS j .

III. UES AND BSS IN CARE METHOD

We formulate preferences in the form of utility functions for BSs and UEs in CARE protocol.

A. UEs' Preferences

1) *Link Robustness to Hand-off Failures*: The emerging 5G cellular networks still need practical solutions to enable ubiquitous and reliable connections for fast moving vehicles especially in the densely populated urban areas. The mobile UEs e.g. vehicles need reliable and seamless connections without hand off risk which significantly increases with network densification. Mobile UEs prefer to be assigned to MBS through the wider beams to minimize the number of hand offs. On the other hand maximizing the spatial resources reuse suggests using narrow beams. Thus, we introduce ASTB model in order to provide a compromise between the two above contradicting requirements. The main aim of ASTB is to provide as long as possible a robust links by narrow beams in order to increase the number of mobile users that reuse the resources.

Definition 1. The link robustness $L_{i,j}$ is defined as the expiration time of the connection between BS j and UE i .

The link robustness to hand-off failures depends on beamwidth of BSs in addition to speed, direction and transmission range of UEs. Let O_i be the coordinates of UE i and O_j the same parameter of BS j (relay, AP or MBS). Also let ϑ_i and Z_i be the velocity and transmission range of UE i respectively. Then the time that they will be connected is predicted by

$$L_{ij} = \frac{W_{j,i}}{\vartheta_i} = \frac{\lfloor \frac{\theta_{j,i}}{\theta} \rfloor Z_i \sin \theta_{j,i} + |O_i - O_j|}{\vartheta_i}, \quad (1)$$

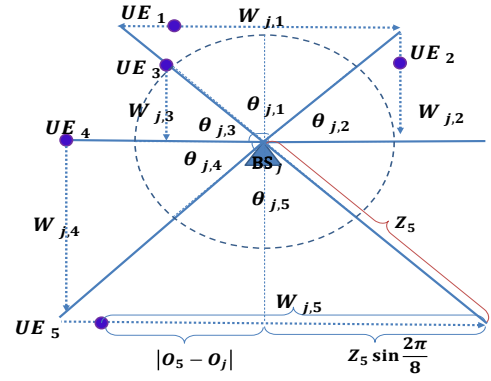


Fig. 2. Adaptive spatial beamforming (ASB) model.

where $W_{j,i}$, $\theta_{j,i}$ represent coverage distance (See Fig.2) and angular beamwidth of BS j for UE i inside the cell respectively. In (1), $\lfloor \frac{\theta_{j,i}}{\theta} \rfloor$ is the number of assigned sub-beams to UE i in addition to the current active sub-beam. To simplify the notations, we assume that all mobile UEs move along the x axis. This models well vehicles moving on the streets. The extension to arbitrary directions is straightforward. In order to improve further the performance of the ASB model shown in Fig. 2 we develop ASTB scheme in order to assign sub-beams in different time slots based on the location of mobile users. We denote by V sub-beam allocation matrix, where $V_{y,x}(k, \delta)$ is one if sub-beam k -th of BS y is assigned to UE x in time slot δ , otherwise zero.

2) *Throughput*: For static UEs, hand offs related to the allocated beamwidth is not of primary importance and the main concern is throughput. They like to be assigned to the nearest BSs to achieve the maximum throughput. For every UE, capacity of link between transmitter x and receiver y with beamwidth $\theta_{y,x}$ can be calculated by

$$C_{x,y} = \sum_{sc \in SC} \sum_{\delta=1}^{\Delta} \sum_{k=1}^{\zeta} \omega_{sc} \log \left(1 + \frac{P_x D_{x,y}^{-\alpha} V_{y,x}(k, \delta)}{N_0 + \gamma_y(\eta, \theta_{y,x})} \right), \quad (2)$$

where ω_{sc} , P_x , $D_{x,y}$ and N_0 represent bandwidth of sub-carrier sc , transmit power of x , distance between (x, y) and noise respectively. In the above, $\gamma_y(\eta, \theta_{y,x})$ represents the aggregated interference to receiver y from the set of simultaneous communications in the matching function η under beamwidth $\theta_{y,x}$. As will be discussed in Section IV, η defines the optimum (matched) selection of connections between UEs and APs. We will show, in the next section, that η includes communications of both access and backhaul networks. In (2), Δ represents the maximum available number of time slots and $P_x D_{x,y}^{-\alpha} V_{y,x}(k, \delta)^2$ is the received power according to the allocated beamwidth $\theta_{y,x}$. In general received signal strength is proportional to $D_{x,y}^{-\alpha} V_{y,x}(k, \delta)^2$, where α is the pathloss exponent.

3) *Delay*: To experience lower delay, UEs avoid overloaded-BSs or multihop paths. In the proposed framework, each UE i experiences a delay τ_i given as

$$\tau_i = \tau_{i,j}^A + \tau_{j,j'}^B, \quad j \in \mathcal{R}, j' \in \mathcal{A} \cup \mathcal{M}, \quad (3)$$

where $\tau_{i,j}^A$ and $\tau_{j,j'}^B$ represent the access and backhaul delays of UE i and relay j respectively. Here, we assume that UE i

having an arrival rate λ_i transmits its traffic through BSs j and j' to Internet. If UE i is directly communicating with either AP or MBS, $\tau_{j,j'}^B = 0$. Thus, delay of every UE i connected to BS j in access network can be calculated as

$$\tau_{i,j}^A = \frac{1}{\kappa_j - \lambda_i - \sum_{i' \in \mathcal{I}_j \setminus i} \lambda_{i'}} \quad j \in \mathcal{R}, \quad (4)$$

where κ_j represents service rate of BS j which is a relay and \mathcal{I}_j the list of UEs assigned to BS j . In the backhaul network, UEs and relays may be associated to the BSs. Therefore, for a given BS $j' \in \mathcal{A} \cup \mathcal{M}$ that serves a subset of UEs $\mathcal{I}_{j'} \subset \mathcal{I}$ and relays $\mathcal{R}_{j'} \subset \mathcal{R}$, the backhaul delay for a relay $j \in \mathcal{R}_{j'}$ can be calculated as

$$\tau_{j,j'}^B = \frac{1}{\kappa_{j'} - \lambda_j - \sum_{x \in \mathcal{I}_{j'} \cup \mathcal{R}_{j'} \setminus j} \lambda_x}, \quad j' \in \mathcal{A} \cup \mathcal{M}, \quad (5)$$

where $\mathcal{R}_{j'}$ is the subset of relays associated with BS j' . In (4) and (5), BSs experience a longer delay if they acquire less link capacity (smaller service rate) in access and backhaul networks. By assuming all UEs have a same arrival rate λ , we can reformulate (3) as

$$\tau_i = \frac{1}{\kappa_j - |\mathcal{I}_j| \lambda} + \frac{1}{\kappa_{j'} - |\mathcal{I}_{j'}| \lambda - \sum_{r \in \mathcal{R}_{j'}} |\mathcal{I}_r| \lambda}, \quad (6)$$

where \mathcal{I}_r is the set of UEs using relay $r \in \mathcal{R}_{j'}$. For a single-hop scenario without relaying, delay can be calculated by $\tau_i = 1/(\kappa_j - |\mathcal{I}_j| \lambda)$. Notice that service rate of every BS can be calculated by (2) based on the current matching function η [14].

B. BSs' Preferences

For BSs, the main concern is enhancing sum-rate for increasing the resource utilization ratio while all UEs' requirements are met. For every BS j , the throughput C_j can be calculated by

$$C_j = \min(C_j^{in}, C_j^{out}), \quad (7)$$

where C_j^{in} and C_j^{out} are the input and output throughput for BS j respectively. Deploying relays can efficiently improve the throughput of BSs in addition to utility of UEs.

C. UEs' and BSs' utilities

The aim of each BS is to maximize its own utility, or equivalently be associated with the most preferred UEs. The maximum capacity C_j (7) of every BS j can be reformulated as

$$C_j = \min\left(\sum_{i \in \mathcal{I}_j} C_{i,j}, C_j^{out}\right) \quad (8)$$

where $C_{i,j}$ represents the capacity of BS j over link (i, j) . In the above, C_j^{out} for the relays is calculated by (2). In (8), the set of UEs connected to BS j is indicated by \mathcal{I}_j . We define utility of BS j as follows,

$$U_j(\eta) = X_j C_j - E_j, \quad (9)$$

where X_j is a positive constant and E_j represents the energy consumption under matching function η .

Every UE concerned about delay, throughput or link robustness considers a different utility function to optimize. We formulate the following utility functions for a UE i associated with BS j and preference for:

a) Capacity:

$$U_i(j; \eta) = \min(C_{i,j}, C_j) [\min(C_{i,j}, C_j) - C_i^{th}]^+ - e_{i,j}$$

b) Robustness:

$$U_i(j; \eta) = L_{i,j} [\min(C_{i,j}, C_j) - C_i^{th}]^+ - e_{i,j}$$

c) Latency:

$$U_i(j; \eta) = \frac{[\min(C_{i,j}, C_j) - C_i^{th}]^+}{\tau_i} - e_{i,j} \quad (10)$$

where $e_{i,j}$ represents the required power consumption for the link between UE i and BS j . We use term $[\min(C_{i,j}, C_j) - C_i^{th}]^+$ to assure that every mobile UE gets a minimum capacity C_i^{th} . The symbol $[\]^+$ returns 1 if $\min(C_{i,j}, C_j) \geq C_i^{th}$, otherwise 0.

With all this in mind, we formulate CARE as the following optimization problem:

$$\begin{aligned} \text{Problem 1 : } & \max_{\mathcal{V}} \sum_{i \in \mathcal{I}} U_i + \sum_{j \in \mathcal{J}} U_j \\ \text{s. t.} & \\ & a) C_i \geq C_i^{th} \in \mathcal{I}^C, \\ & b) L_i \geq L_i^{th} \in \mathcal{I}^R, \\ & c) \tau_i \leq \tau_i^{th} \in \mathcal{I}^L, \end{aligned} \quad (11)$$

where \mathcal{J} , \mathcal{I}^C , \mathcal{I}^R and \mathcal{I}^L represent the sets of BSs (APs and relays and MBs), UEs which are concern about capacity, robustness and latency respectively. The optimization problem is combinatorial and difficult to solve even for a small network. In this paper, we propose a two-step matching game model to tackle this difficulty.

IV. A TWO-STEP MATCHING GAME (TSM) FOR CONTEXT-AWARE RESOURCE ALLOCATION (CARE)

A. Two-Step Matching Game

To solve Problem 1, we divide the main association problem into two sub-matching games: access and backhaul networks sub-matching games (See Fig.3).

In the access network, a many-to-one sub-matching game (AMG) between UEs and BSs is developed, where BSs use the proposed ASTB scheme to serve UEs with different beamwidth in space-time domains. A stable sub-matching (SSM) η^A between UEs and BSs is the solution of this sub-game such that there is not any player who likes to change its matching. In the backhaul, a many-to-one sub-matching game (BMG) is defined between relays and APs/MBSs, where relays try to find a better option to transmit their aggregated traffic. Again, a stable sub-matching (SSM) η^B between relays and APs/MBSs is the solution of this sub-game. Initially, relays are associated to APs/MBSs to create the backhaul network structure, where associating relays to the nearest APs or MBSs is a reasonable initialization for this sub-matching

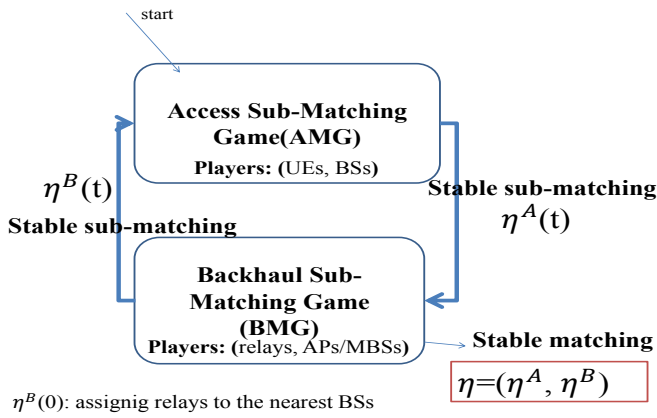


Fig. 3. The proposed two-step matching game.

game. Then, the UE-BS matching game is launched to satisfy both UEs and BSs in the access network. These two steps are sequentially repeated until both games converge to a stable matching $\eta = (\eta^A, \eta^B)$, where players in access and backhaul networks have no incentive to leave their current matching. In Fig.3, $\eta^A(t)$ and $\eta^B(t)$ represent the stable sub-matchings in the t -th iteration for the access and backhaul sub-matching games.

To solve the proposed two-step matching game in CARE, we propose Algorithm 1, having three different steps.

Algorithm 1 Two-Step Matching Games in CARE

- 1: **Step 1:**
 - 2: $t=1$
 - 3: $\eta^B(0)$ includes all relays associated to the nearest BSs.
 - 4: **Step 2:**
 - 5: Find a stable sub-matching $\eta^A(t)$ for access network with given backhaul sub-matching $\eta^B(t-1)$.
 - 6: **Step 3:**
 - 7: Find a stable sub-matching $\eta^B(t)$ for backhaul network with given access sub-matching $\eta^A(t)$.
 - 8: If $\eta^B(t) == \eta^B(t-1)$ and $\eta^A(t) == \eta^A(t-1)$, $\eta = (\eta^A, \eta^B)$ go to END else $t = t + 1$ and go to step 2.
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B. Access and Backhaul Sub-Matching Games

To properly model the association sub-problems in the access and backhaul networks, we define a many-to-one sub-matching game model as

Definition 2. A many-to-one sub-matching game model η^X , $X \in \{A, B\}$ is defined by two sets of players ($\mathcal{X} = \{\mathcal{I}, \mathcal{R}\}$, $\mathcal{Y} = \{\mathcal{R}, \mathcal{A} \cup \mathcal{M}\}$) such that $\forall x \in \mathcal{X}$ and $\forall y \in \mathcal{Y}$: 1). matching function $\eta^X(x) \in \mathcal{X}$, $|\eta^X(x)| \leq 1$, 2). $|\eta^X(y)| \leq \zeta_y$ where $\zeta_y = \zeta \times \Delta$ is the quotas of BS y , and 3). $\eta^X(x) = y$, if and only if x is in the $\eta^X(y)$.

In access network ($X = \{A\}$), $\mathcal{X} = \{\mathcal{I}\}$ and $\mathcal{Y} = \{\mathcal{R}\}$ while for backhaul network ($X = \{B\}$), $\mathcal{X} = \{\mathcal{R}\}$ and $\mathcal{Y} = \{\mathcal{A} \cup \mathcal{M}\}$. The UEs which are not assigned to any BS, need extra resources e.g. channel frequencies and relays/APs. Here, we use time scheduling to allocate the same frequency in different time slot. The idle relays also are switched off to save energy.

The sub-matching functions η^A and η^B bilaterally assign to each player $y \in \mathcal{Y}$, a subset $\mathcal{X}_y \subset \mathcal{X}$ of UEs and relays respectively, $\mathcal{X}_y = \eta^X(y)$, and every player x is associated at most to one BS y i.e. $y = \eta^X(x)$.

A preference relation \succ is defined as a complete, reflexive, and transitive binary relation between the players in $(\mathcal{X}, \mathcal{Y})$. Let $U_x(\bullet)$ and $U_y(\bullet)$ denote the utilities of players $x \in \mathcal{X}$ and $y \in \mathcal{Y}$ respectively. Thus, for any x in the sub-matching game, a preference relation \succ_x is defined over the set of \mathcal{Y} in such a way that for any two player $y, y' \in \mathcal{Y}$, $y \neq y'$, and two matchings η^X, η'^X , $y = \eta^X(x)$, $y' = \eta'^X(x)$:

$$(y, \eta^X) \succ_x (y', \eta'^X) \Leftrightarrow U_x(\eta^X) > U_x(\eta'^X) \quad (12)$$

If player x gains better payoff with BS y rather than with BS y' , it prefers to be matched with BS y . The player x sends a proposal to BS y to be associated with it. BS y evaluates proposal list to select the top-ranked offer and refuses the rest. Therefore, for any BS y in the sub-matching game, a preference relation \succ_y is defined over the set of \mathcal{X} and the subset of players \mathcal{X}_y served by BS y in such a way that for any two players $x, x' \in \mathcal{X}$, $x \neq x'$, and two matchings η^X, η'^X , $\mathcal{X}_y \cup x = \eta(y)$, $\mathcal{X}_y \cup x' = \eta'(y)$:

$$(x, \mathcal{X}_y, \eta^X) \succ_y (x', \mathcal{X}_y, \eta'^X) \Leftrightarrow U_y(\eta^X) > U_y(\eta'^X) \quad (13)$$

BS y which is serving \mathcal{X}_y prefers player x to x' , if it gets better payoff. To solve the many-to-one sub-matching games, we propose Algorithm 2, which generates a stable matching as solution. A new association m can be added to the current

Algorithm 2 Access/Backhaul Sub-Matching game in CARE

- 1: $\delta = 1$, $\eta = \{\}$, $\eta^X = \{\}$ and $m = \{\}$
 - 2: **Step 1:**
players in \mathcal{X} and \mathcal{Y} broadcast their updated information according current η^X and η .
 - 4: UEs/relays rank BSs and UEs.
 - Step 2:**
 - 6: Every player $x \in \mathcal{X}$ sends proposals to its top-ranked player in \mathcal{Y} .
 - Step 3:**
 - 8: Every player $y \in \mathcal{Y}$ chooses player $x \in \mathcal{X}$ optimizing utility from its list of proposal.
If the assignment $m(x \rightarrow y)$ is approved by the affected players in \mathcal{Y}_m ,
- $$U_q(\eta \cup m) \geq U_q(\eta), \quad \forall q \in \eta \cap \mathcal{Y}_m, \quad (14)$$
- go to next else go to Step 3.
- 10: **Step 4:**
If m does not include any association and there are un-served UEs, $\delta = \delta + 1$ and go to step 1.
 - 12: Add the new associations m to η^X and refuse the all affected proposals.
If there is no un-served player, go to END else go to step 1.
-

matching function η^X if and only if it does not degrade the minimum requirements of the previous associations in η .

V. TWO-STEP STABLE MATCHING AND NASH STABILITY CONCEPTS IN CARE

A. Two-Step Matching Game

For the proposed many-to-one sub-matching games in the access and backhaul networks, a suitable solution is a two-step stable matching η which is defined as:

Proposition 1. *A sub-matching η is said to be two-step stable matching (TSSM), if there is not any pair of players $x, x' \in \mathcal{X}$ which are associated under η to BSs $y, y' \in \mathcal{Y}$ respectively, where BS y' prefers x to x' , i.e., $x \succ_{y'} x'$ and at the same time, player x prefers y' to y , i.e., $y' \succ_x y$. In simple terms, η is TSSM if and only if both sub-matching games η^A and η^B are stable.*

Proof. In a stable matching η there is not BS and UE which like to break their current associations. According to Algorithm 1, η is achieved if both access and backhaul sub-matching games are stable, otherwise η is not stable. \square

Proposition 2. *Starting from the first step in Algorithm 2, the proposed many-to-one matching game, including the steps two and three, is guaranteed to converge to a stable matching η^X in a reasonable time.*

Proof. First, every sub-matching game of access or backhaul networks is separately considered with assuming the other subgame is in a stable matching. Second, during the many-to-one matching game every player is assigned with its top-ranked player according to the updated matching function if the new assignment is approved by affected players. Finally, every player due to the limited transmission range and ASBS model is able to reach or affect a finite number of players. Thus, the proposed matching game has a reasonable complexity and can converge in a reasonable time. \square

B. Further Improvements by Coalition Games

The solution provided by Algorithm 1 should be checked if players can improve further their utility or not since sub-beams of BSs are assigned independently to UEs and BSs during each time slot (optimal per each time slot). We formulate their decision making process as a coalition game [15], [16], [17], [18]. Here, we develop a coalition game for the matching $\eta = (\eta^A, \eta^B)$ with players \mathbb{L} as

Definition 3. *A coalition game $\mathbb{G} = (\mathbb{L}, \mathbb{U})$ is defined by a finite set of players $\mathbb{L} = \mathcal{I} \cup \mathcal{J}$, and \mathbb{U} as a partition function (utility function of players) that maps to every coalition a payoff vector that players can achieve.*

In the proposed coalition game, a coalition consists of UEs and BSs which are active during a specific time slot. UEs and relays as players decide to join the best coalition. APs and MBSs as the leaders make decision based on who can give higher payoff by joining their coalitions. Every member of these coalitions can make two different transfers: Inter-coalition (one time slot) or Intra-coalition (two different time slots). These two different transfers can harm current

association in the matching function due to the externality. Thus, we use Pareto optimality concept as a solution for the proposed coalition game $\mathbb{G} = (\mathbb{L}, \mathbb{U})$. Intuitively a coalition is Pareto optimal if no player can be better off without requiring another player to be worse off.

Proposition 3. *A set of coalitions, \mathcal{S} , resulting from coalition game $\mathbb{G} = (\mathbb{L}, \mathbb{U})$ is said to be Pareto Optimal, if the following two conditions do not hold, where \mathcal{S}' is the blocking coalition.*

$$\begin{aligned} (1) \quad & U_q(\mathcal{S}') \geq U_q(\mathcal{S}), \quad \forall q \in \mathcal{I} \cup \mathcal{J}, \\ (2) \quad & U_q(\mathcal{S}') > U_q(\mathcal{S}), \quad \exists q \in \mathcal{I} \cup \mathcal{J}. \end{aligned} \quad (15)$$

Proof. Equation (15) indicates the blocking set \mathcal{S}' , where utility of all players are not degraded and at least one player gets more payoff. Thus, if there is not a blocking set for a coalition, it is a Pareto optimality. Notice that a sub-coalition $\mathcal{S}_j \in \mathcal{S}$ is stable if there is not any relay and UE having incentive to do either Inter or Intra-coalition transfers. \square

The Pareto optimality concept makes sure that a new coalition can be created if at least one player improves its utility while other players will not reduce their profit. This concept limits the freedom of players to leave or join to the coalitions because we assume that all player use the same channel frequency for their transmissions.

Here, we introduce Nash stable concept as a suitable solution of coalition game.

Theorem 1. *A strategy η^* is called Nash stable if no player can benefit from leaving current coalition to join another existing coalition. In other words, η^* is called Nash stable if and only if η^{*A} and η^{*B} are Nash stable for sub-matching games in access and backhaul networks respectively. A strategy η^* is called a Nash stable, $\forall i, i' \in \mathcal{I}, \forall r, r' \in \mathcal{R}$, if there is not any player in $\{i, i', r, r'\}$ that can benefit when moving from his current matching η^* to another matching η .*

$$\begin{aligned} (1) \quad & (i, \eta^*) \succ_r (i', \eta) \leftrightarrow U_r(i, \eta^*) \geq U_r(i', \eta), \\ (2) \quad & (r, \eta^*) \succ_i (r', \eta') \leftrightarrow U_i(r, \eta^*) \geq U_i(r', \eta). \end{aligned} \quad (16)$$

Proof. Assume η^* is a Nash stable point for players. Then, if there exist some players which can improve their utility by leaving their current matched players in either η^{*A} or η^{*B} , η^* is not a Nash stable. This violates our initial assumption. \square

Nash stability provides an ideal framework for the solution of coalition game, where players can not improve their utilities anymore. We develop the distributed Algorithm 3 for coalition game between UEs and BSs, to find a Nash stable coalition

for the association problem. The Algorithm 3 is composed of two main steps: *Update* and *Transfer*. First, every UE and BS updates preference list based on current coalitions. Then, every UE and relay send a proposal to top-ranked BSs. BSs exchange proposal list with their neighbour BSs to find the best options for transferring.

Lemma 1. *Algorithm 3 reaches a Nash stable coalition.*

Algorithm 3 Coalition game for CARE+

- 1: Step 1:
- 2: According to η resulting from the matching game, the set of coalitions \mathcal{S} is updated.
- 3: Step 2:
- 4: Repeat
- 5: UEs and BSs update their preference lists.
- 6: Every UE (if it has incentive) sends a proposal to another BS.
- 7: Every relay (if it has incentive) sends a proposal to another AP/MBS to join another coalition.
- 8: BSs (APs, MBSs and relays) locally exchange their proposal list to find UE/relay optimizing their utility and reject the rest
- 9: Until convergence to a Nash stable coalition.

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Simulation Area	1000^2
ζ	2,4,6,8
i	10 Packet/sec
I	5-40
J	5-20
δ (time slot)	1×10^{-6}
α	2
Speed(m/s)	50-100
Transmission power	30 dBm
UEs' and BSs' positions	random

Proof. First, every UE and relay can reach a limited number of BSs in the vicinity due to their limited transmission range and the proposed ASBS model. Thus, the number of Inter-coalition transfers is finite. Moreover, only the Inter-coalitions which strictly improve a player's (either relay or UE) utility can occur. All the possible Inter-coalitions and Intra-coalition transfers have been checked. Once there exist no player to have incentive to move to another coalition, no further improvement can be achieved. \square

VI. NUMERICAL RESULTS AND ANALYSIS

In this section, we present numerical results to validate the theoretical analysis of the previous sections and provide some further insights into the operation of CARE. In the analysis we use random network topology with parameters from Table I.

Fig.4 presents sum utility defined by (11) for a scenario with 10 BSs. As expected, in these figures the proposed ASTB mechanism improves significantly the performance of the basic CARE with ASB scheme. By increasing ζ from 4 to 8, depending on the number of UEs, sum utility is increased at least by factor 2. The CARE+-ASTB method with $\zeta = 8$ can enhance the performance of CARE-ASTB with the same parameters between 6% to 95% by Algorithm 3 (marker 1 in Fig. 4). We can improve at least 50% the performance of CARE-ASB ($\zeta = 4$) by using ASTB scheme. By using time domain beamforming, every BS is able to efficiently serve UEs with different requirements. Using a larger ζ and time-space domain beamforming technique can increase the performance of CARE-ASB ($\zeta = 4$) at least by factor 2.5 (marker 3).

Fig. 5 shows how the increase of ζ can improve the performance of CARE+-ASTB for mobile and Data UEs. The

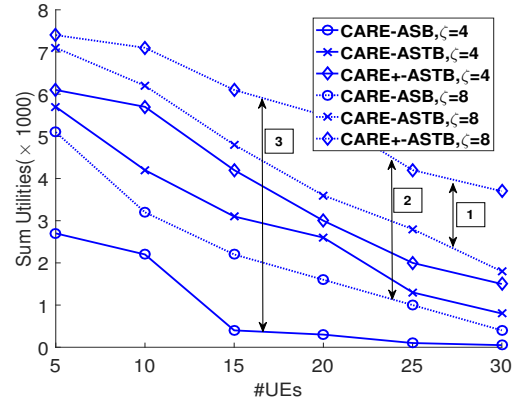


Fig. 4. Sum utility (10) versus the number of UEs with ζ as parameter (BS=10).

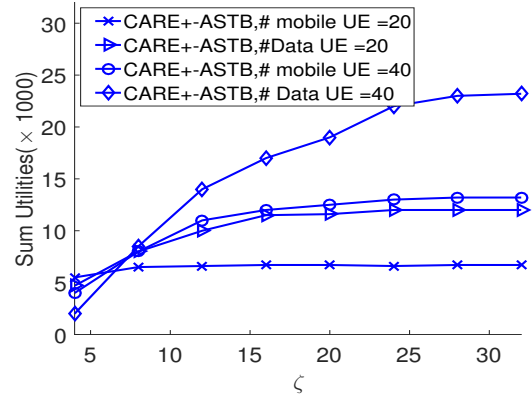


Fig. 5. Sum utility (11) versus ζ with mobile number of UEs as parameter (BS=10, $|\mathcal{I}^C| = |\mathcal{I}^L| = 5$).

Data UEs are referred to those UEs who are concern about data rate. According to the figure, ζ can significantly enhance the network capacity in addition to flexibility to provide robust links for mobile users.

Fig. 6 presents how the proposed algorithms work and how many iterations they require to converge. In the first step, Algorithms 1 & 2 generate TSSM as their output. They need at most 50 iterations to achieve a two-step stable matching game.

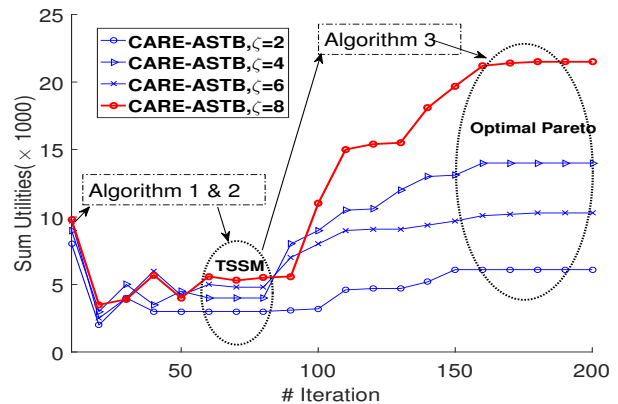


Fig. 6. Sum utility (11) versus the number of iterations with ζ as parameter (BS=10, UE=30).

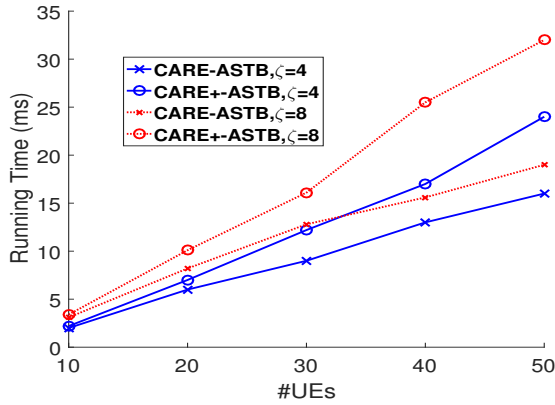


Fig. 7. Running time versus the number of UEs with ζ as parameter (BS=20).

The Algorithm 3 gets TSSM as its initial step and generates an optimal Pareto coalition as its solution. The Algorithm 3 can improve the performance of TSSM by factors between 2 and 5. It optimizes the output of the Algorithms 1–2 over different time slots since they only optimize the resource allocation process per each time slot.

We investigate the proposed algorithms in term of time complexity. We run CARE+-ASTB and CARE+-ASB for bigger scenarios with 20 BSs in order to show how our schemes are practical and scalable. Fig.7 shows that our schemes generate the results very fast even for a big network.

VII. CONCLUSION

In this paper, we develop a self-organized and autonomous context-aware resource allocation approach in such a way that all players with different preferences are satisfied. We use a two-step matching game to develop a scalable UE-BS association with relaying for dense networks with mixed wired and wireless backhaul networks. Furthermore, we propose an adaptive spatial space-time beamforming (ASTB) scheme in order to improve the reuse factor of spectrum in the system. Our numerical results show that CARE+-ASTB algorithm provides about two times higher utility for UEs in comparison to the basic CARE with a reasonable complexity. According to our numerical results, the required number of iterations to find a two-step stable matching and optimal Pareto are about 50 and 160 respectively depending on different parameters. Furthermore, the running time to calculate the two-step stable matching is less than 35 ms for a scenario with 20 BSs and 50 UEs.

As future work, we will consider link redundancy as a parameter in resource allocation mechanism in order to increase link reliability factor in future wireless networks.

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