UNIVERSITY OF CYPRUS

Faculty of Electrical and Computer Engineering

User Association in 5G Networks: A game-theoretic approach

by

Michalis Eliodorou

14/09/2022

Supervisor: Dr. Ioannis Krikids

A dissertation submitted in partial fulfilment of the degree of
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Abstract

In future fifth generation (5G) and beyond 5G wireless technologies, ultra-dense networks (UDNs) will be employed to serve a massive number of devices with mobile access. One of the major challenges in UDNs is user association, which is essential for dealing with intra- and inter-cell interference. In this thesis, two user association problems are investigated and solved via a game theoretical approach. Specifically, the first coalition game exploits the cooperation among the small base stations (SBSs) by utilizing both the zero-force (ZF) beamforming technique and the Non-Orthogonal Multiple Access (NOMA) scheme. A game theoretic algorithm is formulated, aiming to maximize the overall data-rate. Simulation results show that the proposed algorithm can significantly improve the total sum-rate, providing near-optimal solutions while keeping the complexity low. The second coalition algorithm investigates a user association problem for mobile edge computation (MEC) offloading in NOMA networks. NOMA can allow multiple users to access the MEC server to offload data simultaneously. However, resources are shared among the users which can potentially impact the required transmit power for offloading, thus increasing the total energy consumption. Aiming to minimize the overall energy consumption for all the users of the network, we formulate a problem where user association, optimal power allocation, data rate and offloaded data are jointly considered. Simulation results show that the proposed coalition game algorithms can successfully reach a final state with low complexity, where the overall energy consumption is significantly reduced. The effectiveness of coalitional games is shown in this work through the form of algorithms along with their ability to be utilised for resource allocation problems.

Keywords

Game theory, coalition games, resource allocation, user association, mobile edge computing, non-orthogonal multiple access, zero-force beamforming

Chapter 1: Introduction

The constantly increasing number of devices with mobile access and the growing demand of Internet-based services emerging with the development of Internet of Things (IoT), has caused mobile data traffic to grow 18-fold over the past 5 years [6]. To deal with the unprecedented volume of mobile data traffic, 5G and beyond networks must boost their overall throughput. The Cloud-Radio Access Networks (CRAN) is a promising network architecture which can provide coordination among heterogeneous networks (HetNets) and handle resources efficiently [7]. C-RANs are often considered for ultra-dense networks (UDNs), which is an emerging key technology [8]. Nevertheless, UDNs still face many challenges to surpass, due to the deployment of multiple small base stations (SBSs) which can cause severe interference. In C-RAN the information from all SBSs is processed at a centralized base band unit (BBU) pool, which establishes dynamic and flexible resource allocation, including user association. User association is a pivotal mechanism that can, among other things, minimize interference, especially in ultra-dense HetNets were interference can be critical.

In addition, the number of devices keeps increasing year after year and is expected to reach 12.3 billion by the end of 2022 [6]. Even though mobile devices have become more powerful and sophisticated, finite battery life and limited computation capacity pose significant challenges. Due to these limitations, Internet services in fifth generation (5G) and beyond 5G networks cannot be executed solely in isolated devices. Mobile edge computing (MEC) is an emerging key technology derived from the advancements of cloud-computing which is capable of addressing the aforementioned challenges [15]. More specifically, MEC leverages data offloading for execution at a server with superior computation resources deployed at the edge of the network. Another promising technology is non-orthogonal multiple access (NOMA) which allows multiple users to be served simultaneously [16]. The joint implementation of MEC with NOMA gives the advantage that the same resources (i.e. frequency, time, code) are utilized by multiple devices, allowing them to access the MEC server at the same time and execute tasks remotely. However, due to the fact that resources are shared among the users, user association is extremely critical for MEC offloading in NOMA networks. Specifically, it can potentially impact the required transmit power for offloading, critically increasing the total energy consumption.

In our thesis, two coalition games are studied for two different network models where the coalition structure is applied on a set of users. Our aim is to optimise the performance of certain parameters of the system. More specifically, the first work investigates a system model where Zero-forcing and NOMA are jointly considered, and our aim is to provide a user association that maximizes the overall sum-rate. The second part of the thesis applies the coalition structure on a set of users who can apply partial offloading on a MEC server located at a single BS that utilises NOMA. The goal of the formulated game-theoretic algorithm is to minimize the UEs' total energy consumption. The technical contribution of the research work presented here has been accepted and published in two flagship conferences with titles 'User Association

Coalition Games with Zero-Forcing Beamforming and NOMA', IEEE SPAWC 2019 [4] and 'Energy Efficiency for MEC Offloading with NOMA through Coalitional Games', IEEE Globecom 2019 [5].

The rest of the thesis is organized as follows. In Chapter 2, the SotA techniques and research of relevant work is presented along with the two system models describing the formulated problems. The proposed game-theoretic algorithms for each work is presented in Chapter 3 and Chapter 4 respectively. Simulated numerical results are shown in Chapter 5. Finally, in Chapter 6 a conclusion is provided followed by potential future work.

Chapter 2: Literature Review, State-of-the-Art and System Models

In this chapter, we provide the literature review that motivated our research and discuss similar work that has been done recently by the research community for optimizing user association in wireless networks. We explain the SotA techniques that were used in each work followed by the system model. As mentioned above, in our first work, the Zero-Force beamforming technique and the Non-orthogonal Multiple Access scheme are used, and user association is solved for maximizing the overall throughput. In our second work, user association is solved in an attempt to minimize the total energy consumption of the users in an environment where the users are able to execute tasks locally or remotely, through partial MEC offloading.

2.1 User Association using ZF and NOMA for Sum-rate Maximization

Many ways have been considered to solve user association problem. In [9], a greedy user selection algorithm is proposed in a multiuser downlink network with zero-forcing (ZF) beamforming. It is shown that this algorithm performs nearly as well as an exhaustive search scheme. Recent work has shown that game theoretical approaches and, in particular coalition games, are capable of providing low-complexity optimal and sub-optimal solutions to resource allocation problems [10]– [12]. In [10], a coalition game is considered for optimizing the bandwidth allocation, shared between the fronthaul and the backhaul link. In this scenario, the angle of each antenna was optimized to maximize the directivity gain. The authors of [11], propose a coalition game algorithm for non-orthogonal multiple access (NOMA) networks. The optimum weight values for each NOMA pair is evaluated, providing fairness between the strong and the weak user. A coalition game was also designed in [12], aiming to efficiently deploy coordinated multi-point (CoMP) transmissions through cooperation among the network's remote radio heads.

Motivated by the above, in this thesis, we first consider a user association problem in a millimeter wave (mmWave) cellular downlink network with ZF but, in contrast to [9], we solve it as a coalition game. Specifically, we propose an algorithm where both ZF and regularized ZF (RZF) are applied at the small base stations (SBSs), utilizing the ability of these techniques to eliminate intra-cell interference. We show that our algorithm significantly outperforms the conventional minimum-distance association scheme in terms of the network's sum-rate. Furthermore, similar to [11], we exploit the benefits of NOMA, in order to increase the number of users being served. A second algorithm is provided, which implements a coalition game that jointly takes into account ZF and NOMA to associate the users with the SBSs. It is shown that this combination of ZF with NOMA, provides substantial gains to the sum rate performance. The proposed algorithms via coalition games are of great importance for future mmWave HetNets, as they are of low-complexity and can achieve near-optimal solutions. The rest of the thesis is organized as follows.

2.1.1 System Model and Problem Formulation for Maximizing Sum-rate

We consider a downlink mmWave cellular network and focus on a circular area with radius R_D, in which M SBSs and K users are randomly located, with $K \geq M$. We denote by $\mathcal{M}$ = {1, 2, ..., M} and $\mathcal{K}$ = {1, 2, ..., K}, the sets of the SBSs and the users, respectively. Each SBS transmits with power P_t and is equipped with N antennas that can support up to N_{RF} users, where N_{RF} is the number of available radio frequency (RF) chains. Each SBS applies either the ZF or the RZF beamforming technique and utilises the NOMA scheme in the form of pairs. The described system model is shown in Fig. 1. All signals from the SBSs to the users are processed through a BBU pool of a C-RAN architecture.

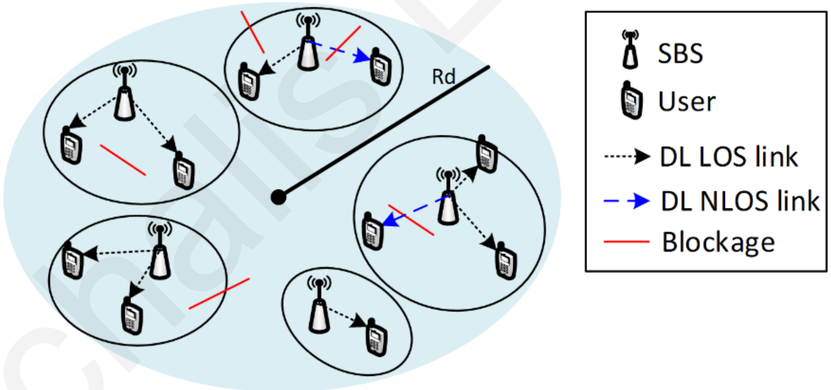

Figure 1 The network model with K = 10 users associated with M = 5 SBS. The solid red lines represent the blockages which indicate if the received signal at the user is LOS (dotted black lines) or NLOS (dashed blue lines).

The set of users associated with the j-th SBS is indicated with $\mathcal{K}_j$ and the cardinality of the set is denoted by K_j, where $K_j \leq N_{RF}$ and $\sum_{j=1}^{M} K_j = K$. The channel matrix of a SBS j $\in \mathcal{M}$ serving K_j users is $H_j = [\boldsymbol{h}_{1,j}^*, \boldsymbol{h}_{2,j}^*, \dots, \boldsymbol{h}_{K_j,j}^*] \in \mathbb{C}^{K_j \times N}$, where $\boldsymbol{h}_{k,j}^* \in \mathbb{C}^{1 \times N}$ is the channel vector of user $k \in \mathcal{K}_j$ associated with SBS j. All channel coefficients are modeled as block Rayleigh fading with unit variance, i.e. $h_{k,j} \sim \mathcal{CN}(0,1)$, and the SBS are assumed to have full channel state information (CSI). The path-loss model is considered to be $d_{k,j}^{-\alpha}$, where $d_{k,j}$ is the distance between user k and SBS j with α being the path-loss exponent. We consider both line-of-sight (LOS) and non-LOS (NLOS) cases for which different values of α are assigned. The probability of a LOS link is $P[LOS] = exp(-\beta d)$, where β is a nonnegative constant, and $1 - P[LOS]$ is the probability of NLOS. The constant β, characterizes the density and length of the blockages [13], presented in Fig. 1. All links contain additive white Gaussian noise with variance σ^2.

The ZF precoding applied at the j-th SBS uses the pseudoinverse of $\boldsymbol{H}_j$, denoted as $\boldsymbol{H}_j^{\dagger} = \boldsymbol{H}_j^{*}(\boldsymbol{H}_j\boldsymbol{H}_j^{*})^{-1}$. In similar fashion, $\boldsymbol{H}_j^{\dagger} = \boldsymbol{H}_j^{*}(\boldsymbol{H}_j\boldsymbol{H}_j^{*} + \frac{\sigma^2}{P_t}\boldsymbol{I})^{-1}$ is applied for the RZF case, where $\boldsymbol{I}$ is the $K_j \times K_j$ identity matrix. For both schemes, the vectors are then normalized producing a new matrix **W**, with weight vectors $\boldsymbol{w}_k$, corresponding to the user k. Then, the signal-to-interference plus- noise ratio (SINR) at the k-th user associated with the m-th SBS is

$$SINR_{k,m} = \frac{\left|\boldsymbol{h}_{k,m}\boldsymbol{w}_k\right|^2 d_{k,m}^{-\alpha}}{I_{k,m} + \frac{\sigma^2}{P_t}}$$

where the value $h_{h,m}w_k$ is the channel coefficient after ZF or RZF precoding. The interference $I_{k,m}$ is

$$I_{k,m} = \mathbb{1}_{RZF} \sum_{\substack{i=1 \\ i \neq k}}^{K_m} \left|\boldsymbol{h}_{i,m}\boldsymbol{w}_i\right|^2 d_{i,m}^{-\alpha} + \sum_{\substack{j=1 \\ j \neq m}}^{M} \sum_{i=1}^{K_j} \left|\boldsymbol{h}_{i,j}\boldsymbol{w}_i\right|^2 d_{i,m}^{-\alpha}$$

where $\mathbb{1}_{RZF} = 1$ if RZF is employed and $\mathbb{1}_{RZF} = 0$ otherwise, since only ZF achieves intra-cell interference elimination by ensuring orthogonality among all the users of the SBS.

In the case where ZF and NOMA are jointly applied, we consider K' additional users which are no longer served with the ZF scheme. NOMA is a multiple access scheme which allows the additional K' users to be served by pairing them with the rest of the initial K users [11]. Each pair requires one strong and one weak user utilizing the same resources apart from the power, which is separated among the users of the pair [14], i.e. the weak user requires more power since its channel conditions are poorer. In this case, the strong user cancels the interference occurred by the weak user's signal, using successive interference cancellation (SIC) techniques [11], while the weak user treats the strong user's signal as interference. We denote by p_w and p_s the power allocation coefficients of the weak and strong user, respectively, with $p_w > p_s$ and $p_w + p_s = 1$. In this case, the SINR of the strong user k, and of the weak user k' are

$$SINR_{k,m} = \frac{p_s\left|\boldsymbol{h}_{k,m}\boldsymbol{w}_k\right|^2 d_{k,m}^{-\alpha}}{I_{k,m} + \frac{\sigma^2}{P_t}},$$

$$SINR_{k',m} = \frac{p_s\left|\boldsymbol{g}_{k',m}\boldsymbol{w}_k\right|^2 d_{k',m}^{-\alpha}}{I_{k',m} + \frac{\sigma^2}{P_t}},$$

where $\boldsymbol{g}_{k',j}^{*} \in \mathbb{C}^{1\times N}$ is the channel vector of user $k' \in \mathcal{K}_j'$. $\mathcal{K}_j'$ is the set of the weak users associated with SBS j and the cardinality of the set is denoted by K_j'. $I_{k,m}$ and $I_{k',m}$ represent the interference affecting the signals of the of the strong user k and the weak user k', respectively, and are

$$I_{k,m} = \sum_{\substack{j=1 \\ j\neq m}}^{M} \sum_{i=1}^{K_j} p_s \left|\boldsymbol{h}_{i,j}\boldsymbol{w}_i\right|^2 d_{k,j}^{-\alpha} + \sum_{j=1}^{M} \sum_{\substack{i=1 \\ i\neq k'}}^{K_j'} p_w \left|\boldsymbol{g}_{i,j}\boldsymbol{w}_i\right|^2 d_{k,j}^{-\alpha}$$

and

$$I_{k',m} = \sum_{j=1}^{M} \sum_{i=1}^{K_j} p_s \left|\boldsymbol{h}_{i,j}\boldsymbol{w}_i\right|^2 d_{k',j}^{-\alpha} + \sum_{j=1}^{M} \sum_{\substack{i=1 \\ i\neq k'}}^{K_j'} p_w \left|\boldsymbol{g}_{i,j}\boldsymbol{w}_i\right|^2 d_{k,j}^{-\alpha}$$

where K_j' indicates the number of weak users served with NOMA by the j-th SBS, with $\mathrm{K}_j' \leq K_j$. We assume that the users served using the ZF scheme are the strong users and that the SIC conditions hold, i.e. $SINR_{k,m} > SINR_{k',m}$.

To formulate the user association problem, we aim to maximize the sum-rate of all small cells, and hence enhance the downlink traffic supported by the network. The data rate of user k served by the m-th SBS is

$$R_{k,m} = B\log_2(1 + SINR_{k,m})$$

where B is the available bandwidth and $SINR_{k,m}$ is calculated as above depending on the case. With the applied ZF/RZF techniques, the SINR of each user can be increased. However, the association of each user is critical as it affects the inter-cell interference caused to the rest of the network's users. Therefore, the overall data rate is highly depended on the user selection. The user association problem based on the utility is formulated as follows

$$\begin{aligned} & \max_{\{\boldsymbol{x}_1,\boldsymbol{x}_2,\dots,\boldsymbol{x}_M\}} \sum_{m=1}^{M} x_{k,m} R_{k,m}, \\ \text{s.t.} \quad & x_{k,m} \in \{0,1\},\ \forall k \in \mathcal{K},\ \forall m \in \mathcal{M}, \\ & \sum_{m=1}^{M} x_{k,m} = 1, \forall m \in \mathcal{M} \\ & \sum_{i=1}^{K} x_{i,m} \leq N_{RF}, \forall m \in \mathcal{M} \end{aligned}$$

where $x_{k,m}$ is a binary value denoting whether or not the k-th user is associated with the m-th SBS and $\boldsymbol{x}_i = \{x_{k,i}\}, k \in \mathcal{K}$, is the set of cardinality K, defining each user's association with the i-th SBS. The second constraint ensures that each user is associated with only one SBS. The third constraint guarantees that the number of users associated with a SBS does not exceed the number of available RF chains, N_{RF}. The formulated problem is non-convex and difficult to transform into a convex problem [11]. However, by treating it as a coalition game the problem can be solved. Our proposed approach for solving the problem using game-theoretic algorithms is presented in Chapter 2.

2.2 User Association using MEC Offloading with NOMA for Energy Minimization

In networks where MEC technology is integrated with NOMA, the energy required by the users to execute a task can be decreased. However, since the resources of the network are being shared among the users, the uplink transmission and the latency play a critical role for minimizing the energy consumption. Many recent papers have considered the application of MEC jointly with NOMA, proposing ways to solve such optimization problems. The authors in [17], improve the energy performance of a multiuser NOMA system with MEC using the Lagrange dual method to obtain the global optimum solution. In [18], the authors investigate a MEC system with one mobile user adopting NOMA to offload data to multiple base stations (BSs), aiming to minimize the total power consumption. The formulated problem is nonconvex and is solved by decomposing it into two subproblems. Another optimization problem, aiming to minimize the maximum overall delay is investigated in [19]. In this work, the authors introduce the relation between resource allocation and uploading delay and propose an algorithm with greedy subcarrier assignment to reduce the overall delay of all users.

As discussed earlier, user association is a mechanism with significant importance for increasing the benefits of NOMA [14], especially in ultra-dense heterogenous networks that are using MEC. MEC is highly affected by resource allocation optimisation and game theoretical approaches have also been applied due to their ability to reach a final state which is beneficial for all players. The authors in [20], propose a low complexity algorithm based on a Stackelberg game to maximize the sum rate of a NOMA system. In this work, it was shown that the proposed scheme is capable of achieving significant performance gain. In [21], a coalition game is considered for optimizing the bandwidth allocation, shared between the fronthaul and the backhaul links, in a mmWave environment. In this scenario, the angle of each antenna was optimized to maximize the directivity gain. The results show that when coalition is adopted the sum-rate is effectively maximized.

Motivated by the above, we investigate another model aiming to minimize the total power consumption for MEC offloading but, in contrast to [18], we formulate the problem for a cellular uplink network with multiple users instead of a single user. In addition, we consider the user-subcarrier association problem, introduced in [19], while also considering the optimization problem for both the rate and the transmit power of each user investigated in [17]. In order to increase the number of users being served we also exploit NOMA. This problem is again formulated and solved via game theoretic tools. Specifically, we propose another two coalition game algorithms that have different initial allocation schemes and different user selection processes to minimize the total energy consumption. The two algorithms are compared showing the benefits of the game-theoretic approach for each case. We show that both algorithms can successfully reduce the energy consumption for both MEC partial offloading and the conventional MEC full offloading.

2.2.1 System Model and Problem Formulation for Minimizing Energy Consumption

We consider an uplink cellular network and this time we focus on only one SBS with N number of subcarriers located at the center of a circular area with radius R_D and K users which are randomly located, with $K \geq N$. We denote by $\mathcal{N} = \{1, 2, \dots, N\}$, the set of subcarriers and $\mathcal{K} = \{1, 2, \dots, K\}$, the set of users. Each user must execute a task with L input bits and is able to offload all or part of the data by utilizing the MEC scheme. In addition, the users of each subcarrier can upload the offloaded data simultaneously using NOMA. Each subcarrier can receive data from up to N_{RF} users at the same time, where N_{RF} is the number of available radio frequency (RF) chains. The described system model is shown in Fig. 2.

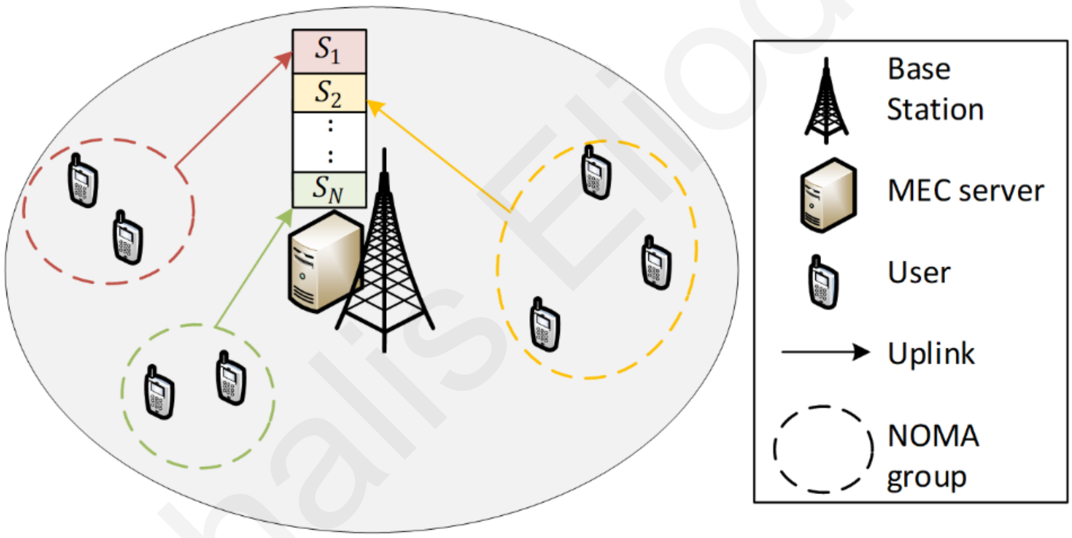

Figure 2 The network model with K users associated with N subcarriers of a SBS co-located with a MEC server at the center. The solid lines represent the UL transmission while the dashed lines indicate group of NOMA users utilising each subcarrier.

The set of users associated with the j-th subcarrier is indicated with $\mathcal{K}_j$ and the cardinality of the set is denoted by K_j, where $K_j \leq N_{RF}$ and $\sum_{j=1}^{N} K_j = K$. The channel vector of a subcarrier $j \in \mathcal{N}$ serving K_j users is

$$\boldsymbol{h}_j = [h_{1,j}, h_{2,j}, \dots, h_{K_j,j}]$$

where $h_{k,j}$ is the channel gain of user $k \in \mathcal{K}_j$ associated with subcarrier j. All channel coefficients are modeled as block Rayleigh fading with unit variance, i.e. $h_{k,j} \sim \mathcal{CN}(0,1)$,and the SBS is assumed to have full channel state information (CSI) for all N subacarriers. The path-loss model is considered to be $d_k^{-\alpha}$, where d_k is the distance between user k and the SBS with $\alpha > 2$ being the path-loss exponent. All links exhibit additive white Gaussian noise with variance σ^2.

We consider a MEC server integrated at the SBS to help users execute their computational tasks within a time slot of duration T. We denote by L the overall bits of the task. The process of remote execution taking place during the distinct period T is partitioned in three phases: T_{UL}, where the user uploads the data to the SBS, T_{EX}, where the processing of the data at the MEC server takes place and T_{DL} for the downlink transmission of the final result back to the user. In this thesis, partial offloading is implemented, meaning that the user can transmit part of the task's bits, $(L-l)$, while the remaining l bits are executed locally. The time block is shown in Fig. 3 and based on the above can be written as

$$T = T_{UL} + T_{EX} + T_{DL}$$

Considering the advanced resources of the SBS and especially the MEC server's high processing capacity, we assume that the time for the execution stage T_{EX} is negligible. In addition, since the data of the result, produced from the remote execution, are considerably small compared to the L number of bits of the task, we assume that the time needed for the final stage has minor impact to the entirety of the time. Based on the above, we assume that $T_{EX} \approx 0$ and $T_{DL} \approx 0$ [17], and we focus on the offloading process, which is the most time-consuming part of the problem.

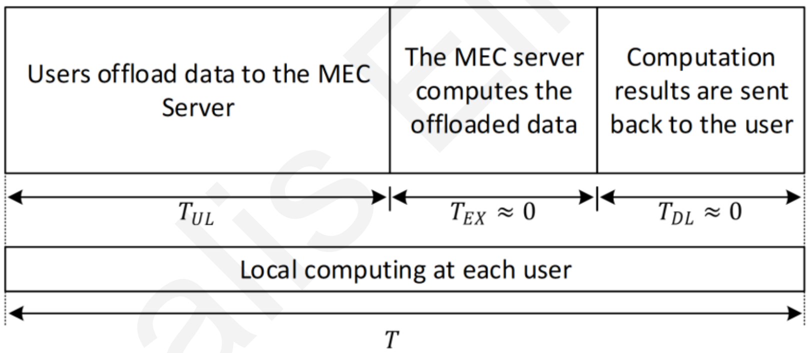

Figure 3 Execution time for partial offloading at the MEC and local computation at the user.

NOMA is a multiple access scheme which can be used for allowing more than one user to offload data simultaneously. In this work, NOMA is applied at each subcarrier, hence K_n users can be assigned to the n-th subcarrier, $n \in \mathcal{N}$, utilizing the same resources simultaneously. For each set of users associated with a subcarrier, the users are ordered based on their channel conditions. For ease of use, the index is ordered in an ascending order, hence $|h_1|^2 \leq \cdots \leq |h_{K_n}|^2$, where $k \in \mathcal{K}_n$. The SBS applies successive interference cancellation (SIC) to decode the signal of each user. More specifically, the receiver decodes the information of the users in K_n stages. In the first stage, it decodes the data of the user with the highest index, K_n, treating the signal from all other users as interference. Once the receiver decodes the data of user K_n, it can reconstruct user K_n's signal and subtract it from the aggregate received signal. The receiver can then decode the data of user $K_n - 1$, with interference from all the users with a lower index. The same process is repeated until the last user, i.e. user 1, which has only Gaussian noise

[22]. Using a SIC receiver at the SBS, the signal-to-interference-plus-noise ratio (SINR) of user k associated with the n-th subcarrier is described as

$$SINR_{k,n} = \frac{p_k |h_{k,n}|^2 d_k^{-\alpha}}{\sum_{i=1}^{k-1} |h_{i,n}|^2 d_i^{-\alpha} + \sigma^2}$$

and the rate (bits/sec/Hz) of each user can be expressed as

$$r_{k,n} = \log_2(1 + SINR_{k,n})$$

The capacity region $C(\boldsymbol{p})$ of the uplink channel is characterized by the set of all rates $(r_1, \dots, r_{K_n})$ [22], satisfying the conditions of the polymatroid, i.e.

$$C(\boldsymbol{p}) = \left\{ \boldsymbol{r} \in \mathbb{R}^{K \times 1} : \sum_{k \in \mathcal{J}} r_k \leq \log_2 \left(1 + \sum_{k \in \mathcal{J}} p_k |h_k|^2 \right), \forall \mathcal{J} \subseteq \mathcal{K} \right\}$$

where $\boldsymbol{p}$ is the power allocation vector $[p_1, \dots , p_{K_n}]$. The selection of $\boldsymbol{p}$ must consider the constraints set by the above capacity region.

In this thesis, the user association along with the partial offloading and the power allocation are jointly considered and the problem is formulated as a coalitional game, aiming to minimize the overall energy consumption of all K users of the network. The total energy consumption of a user depends on the transmit power needed for data offloading and the local computation of the remaining data which takes place at the device. The relation between the rate of user k and the number of bits that can be offloaded is

$$r_k \geq \frac{L - l_k}{B\, T},$$

where l_k is the remaining bits of the task which are executed locally, B is the available bandwidth and T is the time of the time block. The necessary energy to transmit the offloaded data is

$$E_k^{\mathrm{tx}} = p_k\, T.$$

The local energy consumption is determined by the computation capability of the user's device, which is related to the central processor unit (CPU) frequency f_k and indicates the number of CPU cycles/second. The energy consumption of the local computation is represented as

$$E_k^{\mathrm{loc}} = \zeta_k\, f_k^3\, T = \frac{\zeta_k\, C_k^3\, l_k^3}{T^2},$$

where frequency f_k can be rewritten as $C_k\, l_k\, / T$, where C_k is the number of instructions cycles per bit, and ζ_k is the coefficient of the processor architecture that indicates the

CPU capabilities of mobile user k. The total energy consumption of the k-th user is expressed as

$$E_k^{\mathrm{tot}} = E_k^{\mathrm{tx}} + E_k^{\mathrm{loc}}.$$

The association between user and subcarrier is critical since it affects the achievable data rate as shown by the capacity region. Therefore, based on the above, the user association problem is formulated jointly with the transmit power allocation $\boldsymbol{p}$, the achievable data rate $\boldsymbol{r}$, and the offloaded data as

$$\min_{\boldsymbol{r},\boldsymbol{p},\boldsymbol{l},\{\boldsymbol{x}_1,\ldots,\boldsymbol{x}_N\}} \sum_{n=1}^{N} x_{k,n}\left(E_k^{\mathrm{tx}} + E_k^{\mathrm{loc}}\right),$$

$$\begin{aligned}
\text{s.t.} \quad & x_{k,n} \in \{0,1\}, \forall\, k \in \mathcal{K}, \forall\, n \in \mathcal{N} \\
& \sum_{n=1}^{N} x_{k,n} = 1, \forall\, n \in \mathcal{N}, \\
& \sum_{i=1}^{K} x_{i,n} \leq N_{RF}, \forall\, n \in \mathcal{N}, \\
& r \in C(\boldsymbol{p})\ with\, r_k \geq \frac{L - l_k}{B\,T}, \\
& 0 \leq p_k \leq P_{\max}, \forall k \in \mathcal{K}, \\
& 0 \leq l_k \leq L,
\end{aligned}$$

where $\boldsymbol{x}_n = \{x_{k,n}\}$, defines the set of users associated with the n-th subcarrier and $x_{k,n}$ is a binary value denoting whether or not the k-th user is associated with the n-th subcarrier. The second constraint ensures that each user is associated with only one subcarrier. The third constraint guarantees that the number of users associated with a subcarrier does not exceed the number of available RF chains N_{RF}. The fourth constraint ensures that the uplink rates lie within the capacity region $C(\boldsymbol{p})$. Finally, the last two constraints ensure the values for p_k and l_k are non-negative and within a permitted maximum value which are denoted as $P_{\max}$ and L, respectively. In case where the fourth constraint cannot be satisfied, we assume that the entire task is executed locally.

The formulated problem is non-convex and difficult to transform into a convex problem. However, as described in [17], the sub-problem using only the last three constraints is convex and the optimal values for $\boldsymbol{r}^*$,$\boldsymbol{p}^*$ and $\boldsymbol{l}^*$ can be obtained. The sub-problem can be solved with numerical tools such as CVX [23] or Gurobi [24]. Treating the formulated problem as a game we can jointly solve the user association problem of the network and the optimization problem of each subcarrier for the power allocation and the set of rates. The proposed coalition game algorithms are presented in Chapter 3 showing that the general formulated problem can indeed reach a solution.

Chapter 3: Coalition Game Formation Algorithms for User Association with ZF Beamforming and NOMA

In this chapter, we present our proposed work for the system model presented in Chapter 2.1.1. More specifically, while applying ZF and NOMA, we propose and formulate algorithms that are based on coalition games to maximize their utilization, hence the total overall data-rate achieved by the network.

The proposed algorithms provide a user association solution by exploiting the cooperation among the SBS to maximize the total sum-rate. Coalition games have been proven to be very efficient in multi-player scenarios [10]-[12],[25]. The formulated problem described above is defined as a coalition game $(\mathcal{K}, \mathcal{X}, \mathcal{R})$ with a non-transferable utility U [25], where $\mathcal{K}$ is the player set consisting of the users, set $\mathcal{X} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_M\}$, is the set consisting of the vectors indicating the user-SBS associations and $\mathcal{R}$ is the achievable data rate of all the players for a given association $\mathcal{X}$.

A partition of the users, among the available SBSs, is denoted by $\mathcal{S} = \{S_1, S_2, \dots, S_M\}$, where S_m is the coalition consisting of the users associated with the m-th SBS. For each coalition $S_m \in \mathcal{S}, m \in \mathcal{M}$, the conditions $S_m \cap S_l = \emptyset, \forall\, m \neq n$ and $\cup_{m=1}^{M} S_m = \mathcal{K}$ are both satisfied. Before we present the proposed algorithms, the following three definitions are introduced.

Definition 1: (Preference condition) For any user $k \in \mathcal{K}$, we use the symbol $\succ_k$ to denote its preference between two different partition sets $\mathcal{S}$ and $\mathcal{S}'$. The binary decision of a user k depends on whether the utility value of the game with the new partition will increase i.e.,

$$\mathcal{S}' \succ_k \mathcal{S} \Leftrightarrow U(\mathcal{S}') > U(\mathcal{S}),$$

where the utility value $U(\mathcal{S})$ is the overall sum-rate given a partition set $\mathcal{S}$.

Definition 2: (Split and merge operation) Given two different partition sets $\mathcal{S}$ and $\mathcal{S}'$, a user $k \in \mathcal{K}$, decides to leave its current coalition $S_m \in \mathcal{S}$, to join another one $S_{m'} \in \mathcal{S}$, where $m, m' \in \mathcal{M}, m \neq m'$, if and only if its preference condition (Definition 1) is satisfied. The split and merge operation can be written as

$$\{S_m, S_{m'}\} \rightarrow \{S_m \setminus \{k\}, S_{m'} \cup \{k\}\}.$$

Note that for the above operation, the user k joins the other partition if $|S_m| < N_{RF}$. Otherwise, a user k in coalition $S_{m'}$ is selected at random and swapped with k based on the following definition.

Definition 3 (Swap operation) Two users are said to be swapped, if and only if, the preference condition (Definition 1) is satisfied for both. Then, the partitions are updated accordingly as

$$\{S_m, S_{m'}\} \rightarrow \{S_m \setminus \{k\} \cup \{k'\}, S_{m'} \setminus \{k'\} \cup \{k\}\}.$$

3.1 Algorithm 1: Coalition game algorithm with ZF/RZF

The first algorithm is based on ZF/RZF. Initially all users are allocated randomly to the available SBSs. At each iteration, a user associated with SBS, say m, is randomly selected. By selecting a different SBS m', $m \neq m'$, thus selecting another coalition, we check if the preference condition is satisfied. In the case where this is true, operations Split and merge or Swap are applied accordingly. The pseudocode of the proposed algorithm is provided in Fig 4.

Algorithm 1 Coalition game with ZF/RZF

Initializing users with a random parition $\mathcal{S}_{ini}$
Denote current partition $\mathcal{S}_c \leftarrow \mathcal{S}_{ini}$
repeat
    Randomly select a user k of coalition $S_m \in \mathcal{S}_c$
    Randomly select a user k' of coalition $S_{m'} \in \mathcal{S}_c$
    if $|S_{m'}| = N_{\mathrm{RF}}$ **then**
        Assume $\mathcal{S}_{tmp} \leftarrow$ swap user k with user k'
        if $\mathcal{S}_{tmp} \succ_k \mathcal{S}_c$ **then**
            $\mathcal{S}_c \leftarrow \{\mathcal{S}_c \setminus \{S_m, S_{m'}\}\} \cup \{S_m \setminus \{k\} \cup \{k'\}, S_{m'} \setminus \{k'\} \cup \{k\}\}$
    else
        Assume $\mathcal{S}_{tmp} \leftarrow$ user k joins $S_{m'}$
        if $\mathcal{S}_{tmp} \succ_k \mathcal{S}_c$ **then**
            $\mathcal{S}_c \leftarrow \{\mathcal{S}_c \setminus \{S_m, S_{m'}\}\} \cup \{S_m \setminus \{k\}, S_{m'} \cup \{k\}\}$
until

Figure 4 Pseudocode for Algorithm 1: Coalition game algorithm with ZF/RZF.

In what follows, proof is provided that Algorithm 1 converges and that is D_p stable.

Convergence: Starting at any initial combination, the user association game of Algorithm 1 is guaranteed to converge at a final state.

Proof: In order to increase the game utility U, the users perform either one of the operations described above, which results in a constantly modifying partition set. Consider two successive iterations i and $i + 1$, and assume that partition S_{i+1} was formed from S_i, after an operation is applied. Both operations, take place if and only if the game utility U is strictly increased. This can be written as

$$S_i \rightarrow S_{i+1} \Leftrightarrow U(S_i) < U(S_{i+1})$$

Therefore, the game utility value is always increasing, that is,

$$S_{ini} \rightarrow S_1 \rightarrow S_2 \rightarrow \cdots \rightarrow S_{fin}$$

where S_{ini} and S_{fin} is the initial and final partition set of the game, respectively. Hence, the sum-rate is guaranteed to improve at each new partition set. Sine the number of players is finite and the number of actions of each player is finite as well, means that the number of partition sets is also finite and is based on the Bell number [26]. Therefore, the sequence of the partition sets formulated by the algorithm is guaranteed to converge to the final state S_{fin}.

D_p *stability*: The final partition set S_{fin} is D_p stable.

Proof: A partition $\mathcal{S}$ is D_p stable, if for any other partition $\mathcal{S}' \neq \mathcal{S}$, $U(\mathcal{S}) > U(\mathcal{S}')$. Suppose the final partition S_{fin} of Algorithm 1 is not D_p stable. Then, there must exist a user $k \in \mathcal{K}$ that prefers to leave its current coalition and join another. This will form a new partition S_{tmp}, where $S_{tmp} \succ_k S_{fin}$ which contradicts the fact that S_{fin} is the final partition. Therefore, the final partition of Algorithm 1 is D_p stable.

Complexity: Each iteration executes K number of computational operations, to calculate the data rate of each user. Assuming Algorithm 1 is performed for C number of iterations, then the complexity of the algorithm is $\mathcal{O}$(CK), which is much smaller compared to the complexity of the exhaustive search.

3.2 Algorithm 2: Coalition game algorithm with ZF and NOMA

The second proposed algorithm considers NOMA as well, meaning that a dominant and a weak user are paired to increase the number of users served by the network simultaneously. Algorithm 1 first executes Algorithm 1 with ZF, associating K users with M SBSs as shown above. Then K' additional users are considered and participate in a second game. Algorithm 2, also pairs the additional K' with the dominant K users, based on the NOMA scheme. Starting from a random pair allocation, with partition $\mathcal{S}_{ini}^{NOMA}$, the coalition game initiates a number of iterations with the K' users as the players of the game.

The algorithm in this case, selects a user $k \in K'$ and activates a split and merge or a swap operation to test a different pairing. Note that the SIC condition must be satisfied to ensure that the pair can apply NOMA. At each iteration the modified partition is compared and gets accepted only when the overall sum-rate is increased. Similar to the previous algorithm, complexity, convergence and stability are all satisfied; therefore, a final partition will be reached within a limited number of iterations converging at a sub-optimal solution. In Fig. 5, the pseudocode for *Algorithm 2* is presented.

Algorithm 2 Coalition game algorithm with ZF and NOMA

Algorithm 1 is executed
Randomly pair K' additional users with the K users of the first game, i.e. S_{ini}^{NOMA}
Denote current partition $\mathcal{S}_c^{\text{NOMA}} \leftarrow \mathcal{S}_{ini}^{\text{NOMA}}$
repeat
  Select a NOMA user k of coaltion $S_m \in \mathcal{S}_c^{\text{NOMA}}$
  if $|S_{m'}| = N_{\text{RF}}$ **then**
    Select a user k' of coalition $S_{m'} \in \mathcal{S}_c^{\text{NOMA}}$
    $\mathcal{S}_{tmp}^{\text{NOMA}} \leftarrow$ swap case of NOMA users k and k'
    if $\mathcal{S}_{tmp}^{\text{NOMA}} \succ_k \mathcal{S}_c^{\text{NOMA}}$ **then**
      $\mathcal{S}_c^{\text{NOMA}} \leftarrow \{\mathcal{S}_c^{\text{NOMA}} \setminus S_m, S_{m'}\} \cup \{S_m \setminus \{k\} \cup \{k'\},\ S_{m'} \setminus \{k'\} \cup \{k\}\}$
  else
    $\mathcal{S}_{tmp}^{\text{NOMA}} \leftarrow$ NOMA user k pairs with a user of $S_{m'}$
    if $\mathcal{S}_{tmp}^{\text{NOMA}} \succ_k \mathcal{S}_c$ **then**
      $\mathcal{S}_c^{\text{NOMA}} \leftarrow \{\mathcal{S}_c^{\text{NOMA}} \setminus S_m, S_{m'}\} \cup \{S_m \setminus \{k\}, S_{m'} \cup k\}$
until

Figure 5 Pseudocode for Algorithm 2: Coalition game Algorithm with ZF+NOMA.

3.3 Coalition game using the Simulated Annealing algorithm:

The Simulated Annealing algorithm (SAA) allows us to approximate the global optimum solution [11] for the formulated user association problem. This is achieved by sometimes allowing the algorithm to accept a new partition set $\mathcal{S}_{i+1}$, even when the utility value of the new partition, i.e. $U(\mathcal{S}_{i+1})$, is lower than the current one, that is, $U(\mathcal{S}_i) > U(\mathcal{S}_{i+1})$. In particular, if the utility value of the game is higher after a swap or a split and merge operation, then the new state is immediately accepted as described above. However, in order to avoid ending up at a local optimum, we use a probabilistic approach, by applying the Metropolis-Hastings algorithm [27], which allows us of accepting a worse user association, hence introducing flexibility to the convergence of the algorithm. The probability of a partition $\mathcal{S}_{i+1}$ being accepted, despite $U(\mathcal{S}_i) > U(\mathcal{S}_{i+1})$, is decided by the following probability

$$P_{SAA} = \tau \exp\left(\frac{U(\mathcal{S}_{i+1}) - U(\mathcal{S}_{max})}{U(\mathcal{S}_{max})}\right),$$

where τ is the temperature of the SAA and $\mathcal{S}_{max}$ is the up to that point maximum sum-rate value. Using a large number of iterations ensures that the algorithm converges to a global optimum partition which is $\mathcal{S}_{max}$.

Chapter 4: Coalition Game Formation Algorithms for Energy Efficiency for MEC Offloading with NOMA

In this chapter, another two algorithms based on coalition games are presented aiming to solve the formulated problem presented in section 2.2.1. The proposed algorithms provide a user association solution by exploiting the cooperation among the subcarriers, while CSI for all UEs is known, to minimize the total energy consumption. A random and a sequential swapping process are explored for this multi-player scenario.

The formulated problem can be defined as a game $(\mathcal{K}, \mathcal{X}, \mathcal{U})$ where $\mathcal{K}$ is the player set consisting of the users, $\mathcal{X} = \{\boldsymbol{x}_1, \dots, \boldsymbol{x}_N\}$ are the sets of associated users for each subcarrier and $\mathcal{U}$ is a non-transferable utility [25]. A partition of the users, among the available subcarriers, is denoted by $\mathcal{S} = \{S_1, S_2, \dots, S_N\}$, where S_n is the coalition consisting of the users associated with the n-th subcarrier. For each coalition $S_n \in \mathcal{S}, n \in \mathcal{N}$, the conditions $S_n \cap S_q = \emptyset, \forall\, n \neq q$ and $\bigcup_{n=1}^{N} S_n = \mathcal{K}$ are satisfied. For both algorithms, the utility function of a coalition m is given by

$$U(S_m) = \{\sum_{k=0}^{K_m} v_k \mid v_k = \frac{1}{E_k^{\mathrm{tot}}}, \forall k \in S_m\},$$

where v_k is the payoff value of user k given the partition $\mathcal{S}$, which indicates that the payoff value of player k is a decreasing function of the energy consumption E_k^{tot}. Before proceeding, it is important to note that the three definitions (Definition 1: Preference condition, Definition 2: Split and merge operation and Definition 3: Swap operation) that were introduced in Chapter 3, are applied in these algorithms in these algorithms as well.

4.1 Algorithm 3: Coalition game algorithm with random swapping

In this coalition game algorithm, all users are initially allocated randomly to the available subcarriers. At each iteration, a user associated with subcarrier, say n, is again randomly selected. By selecting a different subcarrier n', $n \neq n'$, thus selecting another coalition, we check if the above definitions are satisfied. In the case where this is true, split and merge or swap operations are applied accordingly. The pseudocode of the proposed algorithm is provided in Fig. 6. Proof that the algorithm will converge at a final state which is D_p stable is provided in the previous chapter.

Algorithm 3 Random Coalition Game Algorithm

Initializing users with a random parition $\mathcal{S}_{ini}$
Denote current partition $\mathcal{S}_c \leftarrow \mathcal{S}_{ini}$
repeat
  Randomly select a user k of coalition $S_n \in \mathcal{S}_c$
  Randomly select a user k' of coalition $S_{n'} \in \mathcal{S}_c$
  if $|S_{n'}| = N_{\mathrm{RF}}$ **then**
    Assume $\mathcal{S}_{tmp} \leftarrow$ swap user k with user k'
    if $\mathcal{S}_{tmp} \succ_k \mathcal{S}_c$ **then**
      User k leaves S_n and joins $S_{n'}$
      User k' leaves $S_{n'}$ and joins S_n
      Update current partition:
      $\mathcal{S}_c \leftarrow \{\mathcal{S}_c \setminus \{S_n, S_{n'}\}\} \cup \{S_n \setminus \{k\} \cup \{k'\}, S_{n'} \setminus \{k'\} \cup \{k\}\}$
  else
    Assume $\mathcal{S}_{tmp} \leftarrow$ user k joins $S_{n'}$
    if $\mathcal{S}_{tmp} \succ_k \mathcal{S}_c$ **then**
      User k leaves S_n and joins $S_{n'}$
      Update current partition:
      $\mathcal{S}_c \leftarrow \{\mathcal{S}_c \setminus \{S_n, S_{n'}\}\} \cup \{S_n \setminus \{k\}, S_{n'} \cup \{k\}\}$
until

Figure 6 Pseudocode for Algorithm 3: Random Coalition Game Algorithm.

Each iteration executes K number of computational operations, to calculate the energy consumption of each user assuming optimal values for power allocation, offloaded data and rate have been found. When Algorithm 3 is performed for L number of iterations, then the complexity of the algorithm is $\mathcal{O}(LK)$.

4.2 Algorithm 4: Coalition game algorithm with sequential swapping

The fourth proposed algorithm proposed here, has two distinguished characteristics. The first one, is that the initial association is not random. Instead, for each subcarrier n, $n \in \mathcal{N}$, one user is selected first based on the best channel conditions and distance. The selected dominant user is called coalition head (CH) and is guaranteed a significantly low value for the transmit power to offload data. All remaining users are called coalition members (CMs). The second difference is that at each iteration the investigated player is not selected randomly. In contrast, the CHs make proposals and invite the CMs sequentially to join their coalitions. The strategy of any CH in coalition S_i, towards all CMs of different clusters is expressed as

$$\sigma_i = \{S_i | k \in S_j, \forall j \neq i\}$$

and takes place sequentially for all coalitions $n \in \mathcal{N}$. In each iteration, the corresponding answer of any CM is to either accept the proposal and join the coalition of the CH or reject it and remain at the current coalition. Like Algorithm 3, the response is evaluated based on the sum of the two coalition utility values. The response of a CM k in the j-th coalition, S_j, to a CH in the i-th coalition, S_i, where $i \neq j$ is represented as

$$\sigma_{i,k} = \begin{cases} \text{Yes}, & \text{if } U(S_i) + U(S_j) < U(S_i \setminus \{k\}) + U(S_j \cup \{k\}), \\ \text{No}, & \text{if } U(S_i) + U(S_j) \geq U(S_i \setminus \{k\}) + U(S_j \cup \{k\}). \end{cases}$$

The sequential coalition game algorithm is shown in Fig. 7 as Algorithm 4. Similar to the previous algorithm, convergence and stability are satisfied, therefore a final partition will be reached within a limited number of iterations converging to a final solution. In this algorithm, only $K - N$ operations are executed in each iteration, since the association of N selected users (CHs) is pre-determined according to the initial association scheme. Therefore, the complexity of Algorithm 4 is $\mathcal{O}(L(K - N))$ for L number of iterations which is lower than Algorithm 3.

Algorithm 4 Sequential Game Algorithm

Initialization of S_{ini}:
    All CHs are associated with different subcarriers
    All CMs are randomly associated with the subcarriers
Denote current partition $\mathcal{S}_c \leftarrow \mathcal{S}_{ini}$
repeat
    For any CH i of cluster S_i, $i \in \{1, 2, \ldots, N\}$, user i makes a new proposal σ_i to all CMs sequentially
    For any CM k, $k \in S_j, j \neq i$:
    if $|S_i| = N_{\mathrm{RF}}$ **then**
        Select a CM k' of $S_i \in \mathcal{S}_c$ to investigate swap
        if utilities of S_i and S_j are increased **then**
            The proposal is accepted by the CMs k and k'
        else
            The proposal is declined (no operation)
    else
        if utilities of S_i and S_j are increased **then**
            The proposal is accepted by the CM k
        else
            The proposal is declined (no operation)
until

Figure 72 Pseudocode for Algorithm 4: Sequential Coalition Game Algorithm.

Chapter 5: Numerical Results

In this section, numerical results are presented to demonstrate the performance gain of the proposed coalition game algorithms on the overall data rate for the work focusing on maximizing the sum-rate and the work focusing on minimizing the overall energy consumption of the users.

5.1 Results of the proposed algorithms for User Association with Zero-Forcing Beamforming and NOMA

The following parameters were used: $M = 5,\ N = 6,\ N_{RF} = 6, K = 60$ and $\sigma^2 = -90$ dBm. The SBSs and the users are randomly distributed in a cell of radius $R_D = 50$ m. The system bandwidth is considered to be 20 MHz. The path-loss exponents are $\alpha = 2$ for the LOS case and $\alpha = 4$ for the NLOS. The power coefficients of each pair in the ZF+NOMA scheme are set to $p_w = 0.7$ and $p_s = 0.3$ for the weak and the strong user, respectively.

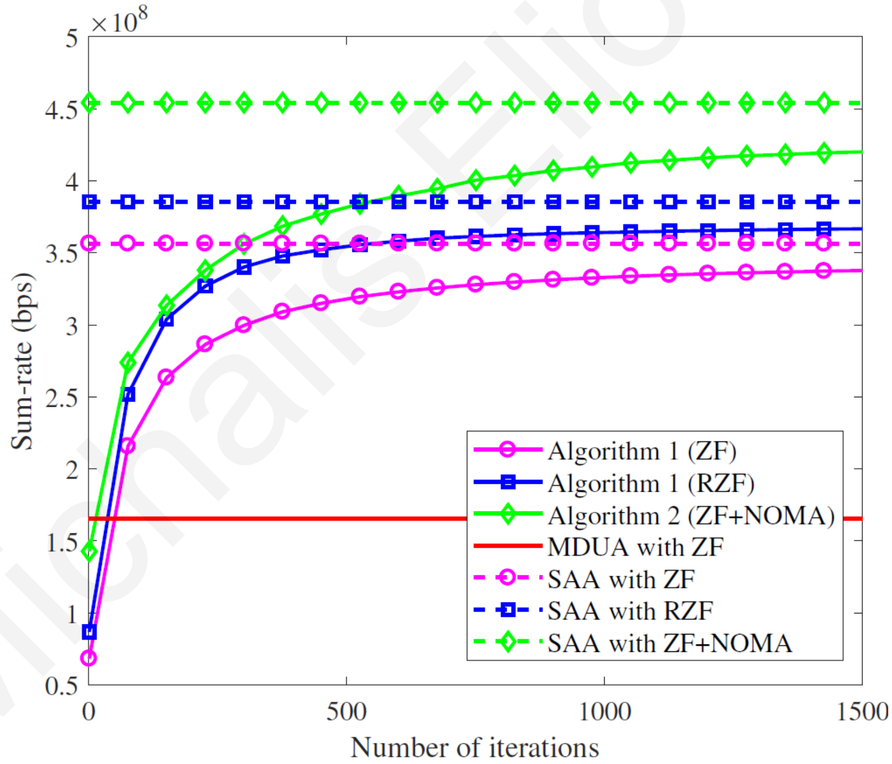

Figure 8 Sum-rate versus the number of iterations.

Fig. 8 shows the system sum-rate achieved by the proposed schemes over the number of iterations along with the minimum-distance based user association (MDUA). As it can be observed from the figure, since the users are initially associated randomly, the sum-rate of both algorithms at iteration 0 is lower than the MDUA scheme. Nevertheless, both proposed algorithms, increase the system's sum-rate as the iteration number increases reaching a final value which is significantly improved compared to the initial one. In addition, a higher sum-rate than MDUA is achieved after just 50 iterations. It is shown that 1500 iterations are sufficient for the game to converge. Algorithm 2 can serve K' additional users, hence the data rate of those users contributes to the overall sum-rate, resulting in a higher value. The SAA algorithm is included with $\tau = 0.2$ to approximate the global optimum value. In contrast with the outstanding low number of iterations required by our proposed algorithms to converge, for the SAA scheme 10^5 iterations were used to ensure that the utility value $U(S_{max})$ approximates the global optimum accurately. Fig. 8 shows that the final values $U(\mathcal{S}_{fin})$ achieved by Algorithm 1 and Algorithm 2, successfully provide a near-optimal solution.

Fig. 9 presents the converged sum-rate value achieved by the proposed schemes along with the MDUA scheme for three different number of users (20, 40 and 60). As we can see, the algorithms outperform the MDUA scheme, regardless of the number of users. The converged value of Algorithm 1 using RZF achieves slightly higher sum-rate compared to the same algorithm with ZF. The ZF+NOMA user association scheme produces significantly higher sum-rate than the rest of the schemes, with the exception of the case of 20 users, where NOMA is not applied as the total number of users can be served with ZF. In our simulations, $MN = 30$, hence for the case of 20 users all the users are served with ZF. This explains why ZF+NOMA has the same value as ZF with 20 users. In the case of 40 users, ZF+NOMA achieves a remarkably higher value than the rest of the schemes. However, in the case of 60 users, even though the ZF+NOMA scheme still outperforms the other schemes, it is lower compared to the performance with 40 users. This shows that the inter-cell interference caused by the additional K' users, in this case, begins to have an impact over the benefits provided by NOMA.

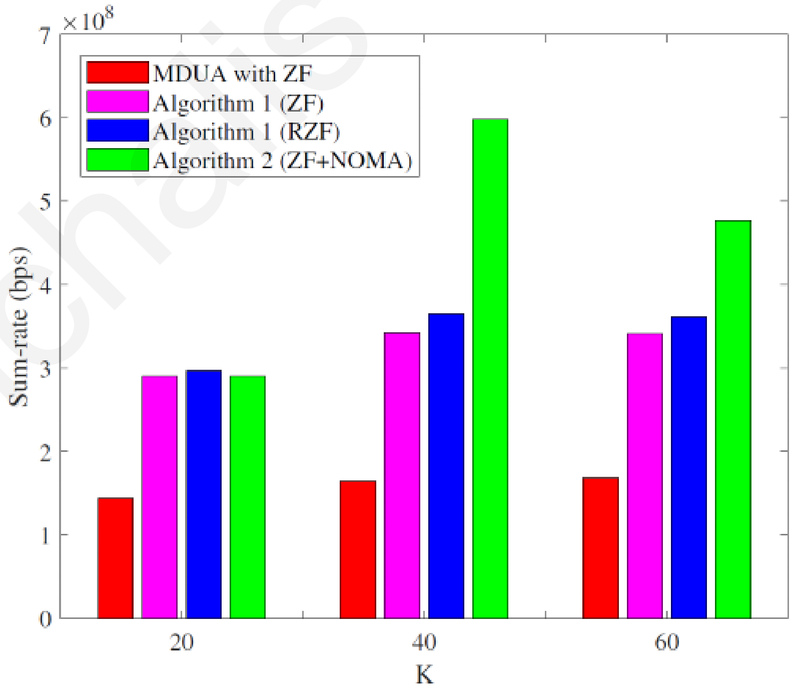

Figure 9 Sum-rate at iteration 1500 versus the number of users.

Focusing on Algorithm 2, three different cases of power allocation $\boldsymbol{p} = [p_w, p_s]$ are presented in Fig. 10, namely [0.7,0.3], [0.5,0.5] and [0.9,0.1]. As it can be observed from the figure, the gains achieved with NOMA are subject to the power allocation. Specifically, while p_s increases, the achievable sum-rate is higher. However, p_w must be considerably higher than p_s to ensure sufficient data rate for the weak users. The case of Algorithm 1 with ZF is also included in Fig. 10. We observe that every ZF+NOMA case in Fig. 10 outperforms the ZF scheme, illustrating the performance improvement achieved with Algorithm 2, where the ZF precoding technique and the NOMA scheme are jointly considered.

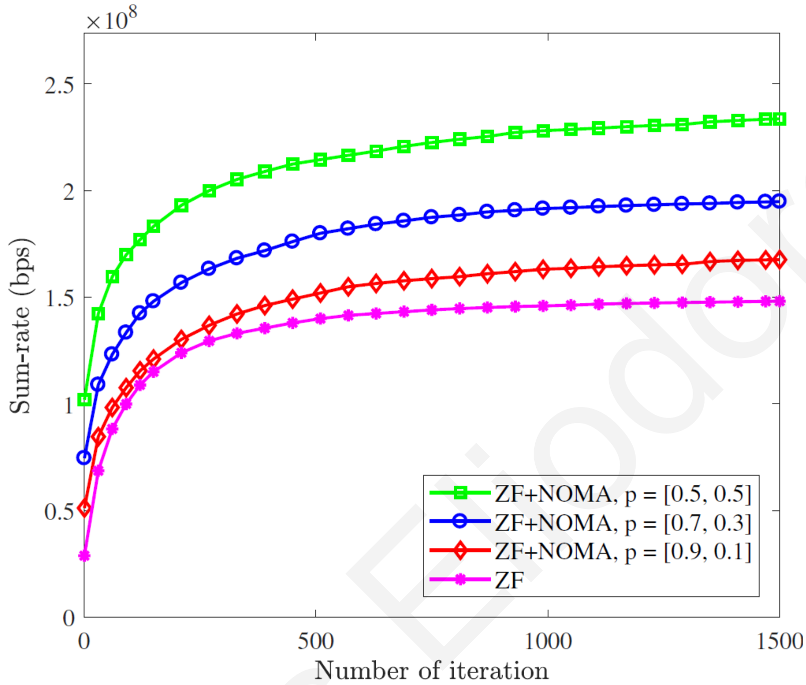

Figure 10 Sum-rate versus the number of iterations for Algorithm 2: ZF+NOMA.

5.2 Results of the proposed algorithms for Energy Efficiency for MEC Offloading with NOMA

In this section, numerical results are presented to demonstrate the performance gains from the proposed algorithms on the total energy of all users. The following parameters were used: $N = 4, N_{RF} = 4, K = 12, \sigma^2 = -90$ dBm and the path-loss exponents is set as $\alpha = 3$. The users are randomly distributed within a cell of radius $R_D = 60$ m. hence the distance between a user and the MEC server can be anywhere between $0 - 60$ m. The random location of the K users is modelled for 100 cases and the average is provided in our results. The bandwidth for each subcarrier is considered to be 200 KHz and the time slot T is 1 sec. The coefficient of the processor architecture is the same for all users with $\zeta_k = 10^{-14}$ and $C_k = 10^3$. The overall number of bits of the task is $L = 200$ bits.

Fig. 11 shows the total energy consumption achieved by the proposed schemes, presented in Section 3, using partial offloading over the number of iterations. We also present Algorithm 3 and Algorithm 4 when applied with full offloading. For the case of full offloading the formulated problem shown is adjusted. Specifically, the constraint for the value of p_k does not include a maximum limit $P_{\max}$ and the constraint related to l_k is completely removed since the offloaded bits are set to L. Along with the algorithms applied for partial and full offloading, the total energy consumption with local computation is included by using the formula of E_k^{loc} with $l_k = L$. As it can be observed, partial offloading provides significant improvement over full offloading and local computation. As the number of iterations increases, the user association changes reaching a final state where both algorithms decrease the total energy consumption. Algorithm 3 can provide a better outcome but requires more iterations than Algorithm 4 which makes the sequential algorithm better for time-critical communication scenarios with mobility. In addition, it can be observed that since the users of Algorithm 3 are initially associated randomly, the initial total energy is higher than Algorithm 4. Finally, for the full offloading case the required energy at iteration 0 is significantly higher compared to the full local computation. However, both proposed algorithms, decrease the system's energy as the iteration number increases reaching a final state which outperforms local computation.

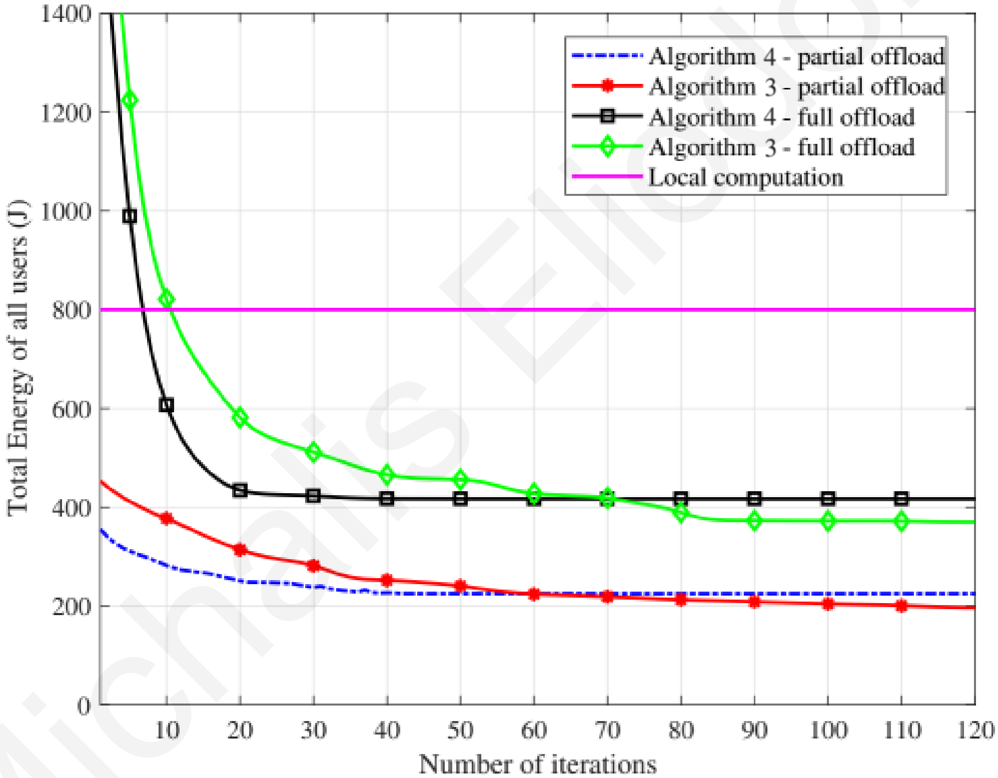

Figure 3 Energy consumption over the number of iterations using Algorithm 3 and Algorithm 4 with partial and full offloading for K=12 users.

In Fig. 12, we show the achievable total energy versus the distance. More specifically, focusing on Algorithm 3, we present the total energy consumption achieved by the algorithm at iteration 100 versus the distance for $K = 8$ users. We point out that the advantages of full offloading are highly affected by the distance. As it can be seen, when the users are close to the BS, the path loss is negligible, hence allowing full offloading to always perform better. However, as the distance of the users increases, the performance of full offloading degrades exponentially. Finally, it is shown that the partial offloading scheme used in our work, will not just converge to a state where the best of the two conventional schemes (local computation or full offload) is chosen, but has the flexibility to combine them. This means that game theoretic approaches for MEC partial offloading can achieve a significant performance improvement for users within the range of 30-70 m.

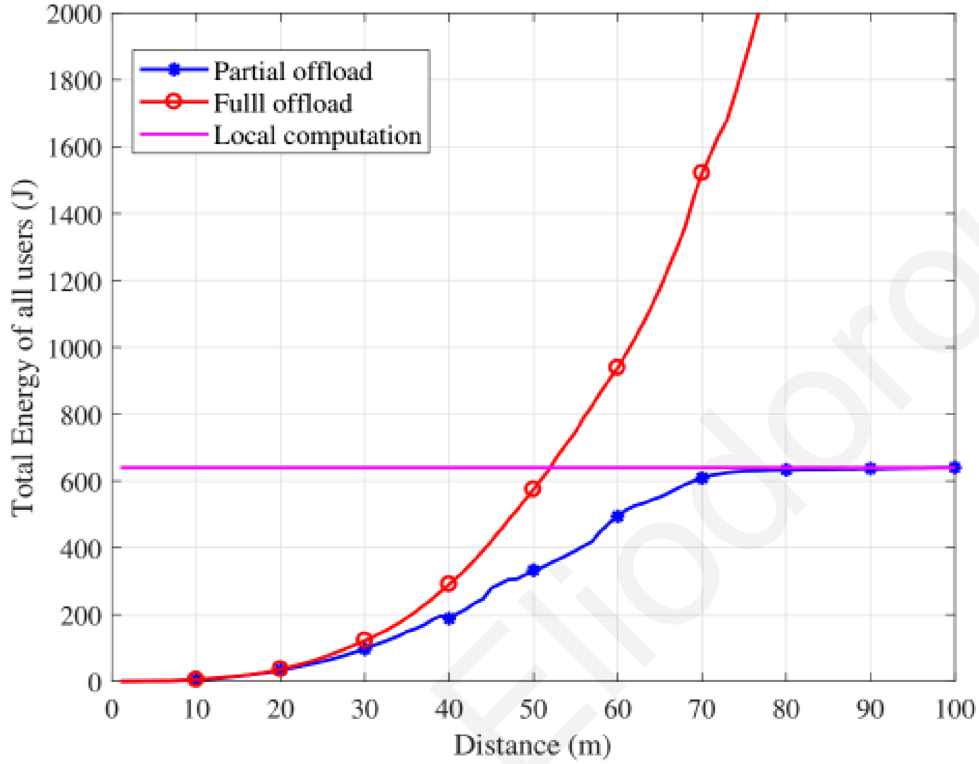

Figure 4 Total energy consumption at iteration 100 of Algorithm 3 versus the distance for K=8 users.

Chapter 6: Conclusion and future work

In this research, we point out that although Cloud-RANs with dense deployment can be very effective for 5G and beyond networks, interference can significantly limit their potential gain. User association schemes can deal with challenges emerging from UDN deployment effectively.

The first part of this thesis proposes a game-theoretic approach that is able to ensure the benefits of the digital precoding technique ZF and the NOMA scheme in downlink, which are both susceptible to user association. The results verify that the proposed coalition game algorithms (Algorithm 1 and 2), can provide near-optimal solutions with low complexity. The final state of the game achieves a significant improvement of the overall sum-rate compared with conventional schemes and increases the number of users being served simultaneously. Future work could also include in the game theoretic algorithm the optimization of the power coefficients applied for each pair using NOMA.

In addition to the sum-rate, another system model where MEC is applied in an uplink NOMA scheme is investigated aiming to minimize the total energy minimization of the UEs. Two more coalition game algorithms (Algorithm 3 and 4) are proposed for optimizing user association while considering the power allocation and the rate of users using MEC offloading in NOMA for uplink. We show the impact of user association and its significance in minimizing energy consumption used for offloading data. Simulation results verify that both proposed algorithms can successfully converge at a final state where the total energy consumption is reduced significantly. Comparison of the two algorithms shows that sequential swapping can reach its final state within a lower number of iterations compared to random swapping. However, random selection provides higher performance gain, reducing the energy consumption even further. The results verify that coalition games are ideal for such optimization problems and the two algorithms can provide solutions with low complexity, efficiently reducing the total energy consumption. A potential extension of this work could also take into account the execution time at the MEC server where a meaningful delay might be present when many users access the server and the performance of the server might degrade. In addition a more complete work could also take into account the time needed within each timeslot for the result to be returned to the UEs.

In addition, expansion and future work could also include a combination of the two models. This will allow a network where multiple users and multiple SBS are participating in the game. User association will aim to benefit both uplink and downlink NOMA schemes and aiming to optimize both the total sum-rate achieved in downlink and the total energy consumption of the UEs for offloading data to the MEC server.

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