Multi-sided Matching for the Association of Space-Air-Ground Integrated Systems

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Abstract—Space-air-ground integrated networks (SAGINs) will play a key role in 6G communication systems. They are considered a promising technology to enhance the network capacity in highly dense agglomerations and to provide connectivity in rural areas. The multi-layer and heterogeneous nature of SAGINs necessitates an innovative design of their multi-tier associations. We propose a modeling of the SAGINs association problem using multi-sided matching theory. Our aim is to provide a reliable, asynchronous and fully distributed approach that associates nodes across the layers so that the total end-to-end rate of the assigned agents is maximized. To this end, our problem is modeled as a multi-sided many-to-one matching game. A randomized matching algorithm with low information exchange is proposed. The algorithm is shown to reach an efficient and stable association between nodes in adjacent layers. Our simulation results show that the proposed approach achieves significant gain compared to the greedy and distance-based algorithms.

Index Terms—Space-air-ground integrated networks, multi-sided matching, blind matching, sum-rate, users’ association.

INTRODUCTION

Space-air-ground integrated networks (SAGINs) emerged as a promising solution to ensure ubiquitous and low-cost connectivity around the globe. Due to their design, flying infrastructure (e.g., satellites, high altitude platforms (HAPs), unmanned aerial vehicles (UAVs)), combined with the terrestrial one, are deployed as one coordinated system to provide high network connectivity in remote and inaccessible areas. SAGINs are also envisioned to support damaged terrestrial infrastructure after a natural disaster, and to extend the network coverage during emergencies and temporary events. Moreover, SAGINs can provide additional backhaul resources to offload backhauling traffic from the terrestrial network. SAGINs also have better energy efficiency compared to traditional terrestrial networks. In particular, satellites and HAPs are generally exposed to consistent solar radiations, which ensures a constant supply of green energy.

Nevertheless, the deployment of SAGINs poses several technical challenges, such as resource allocation, network management and mobility aspects [1]. Although these problems were addressed for standalone spacial/aerial networks and for terrestrial systems, there are still many unanswered questions in combined multi-layered systems. First, compared to traditional networks, SAGINs serve a larger number of users. Thus, the global users’ dynamics change very frequently. This requires fast convergence algorithms to ensure rapid resource allocation. Second, due to the heterogeneous nature of SAGINs, it is important to provide customized resource allocation approaches that adapt with the multi-layered network structure of SAGINs. Therefore, fully distributed mechanisms that do not require coordination and high computational resources are desired.

In the past decade, many works studied resource allocation for aerial and terrestrial networks both separately, as standalone networks, and jointly as an integrated system [2]. Previous works have essentially proposed centralized approaches. In general, the multi-layer optimization is decoupled into sub-problems, each sub-problem is tackled separately using a specific centralized optimization technique [3]–[5]. However, While centralized approaches efficiently solve multi-variate optimization problems, they are not flexible enough to easily adapt to a network of multiple communication layers. Furthermore, they require a centralized entity that coordinates the actions of agents. Such approaches also involve a large amount of overhead and information exchange and require global knowledge of the network.

In this paper, we address reliable resource allocation in SAGINs. Our aim is to provide a distributed, asynchronous and low-computational algorithm that achieves a balanced resource allocation across the multi-tier network while satisfying the network constraints. Game-theoretic modeling, specifically matching theory, is appealing for our problem.

Matching theory started with the work by Gale and Shapley [6] and quickly became an important resource allocation tool, initially for two-sided markets and later for their extensions [7]. There are two main categories within matching theory: marriage markets and transferrable utility games (TU), also called assignment games. The outcome of a TU game is not only the matching but also payoff vectors to the agents that add up to the value that can be generated between the pair of users [8]. We focus on TU games in our model.

One algorithm that serves our purpose of having a decentralized mechanism for resource allocation is the Blind Matching Algorithm (BLMA) in [9]. The authors propose a randomized matching algorithm characterized by probabilistic activation of agents in a two-sided market. Agents have aspiration levels, utilities they currently have or have accrued in the past, that tell them whether a match with another active agent from the other side of the market is better than their current state. This is the only information the agents use to make their
decisions. Despite this knowledge limitation, the algorithm is shown to reach an equilibrium. We use the idea of these blind and random encounters between agents of adjacent layers to associate the agents from different sides of the market.

There are two important solution concepts in matching theory defining equilibrium. Pairwise stability guarantees that two agents cannot form a blocking pair to a matching. Whereas, the core defines the set of feasible payoff vectors which cannot be improved upon by any coalition of players [8]. The two concepts coincide for a number of matching markets. While [9] presents an algorithm to reach a pairwise stable state, equally core-stable, for one-to-one matching markets, extension to the multi-sided case is generally difficult as the core may be empty. However, works like [10] suggest that carefully designing the value generated by a tuple of agents can guarantee non-emptiness of the core.

Hence, we formulate the SAGINs association problem as a multi-sided many-to-one matching market. We design the value generated by a coalition of users in the game so as to guarantee non-emptiness of the core. We then propose a blind and randomized matching algorithm to form groups of agents from the different communication platforms so that the overall utility of the network, the combined rate, is maximized.

Although some works exist in wireless communications on multi-sided matching, it is generally restricted to three-sided marriage markets, e.g., [11], [12]. To the best of the authors’ knowledge, this is the first work within wireless communications that suggests the use of a multi-sided, more than three, matching market with a TU framework, for the SAGINs association problem. The TU framework allows us to jointly optimize the matching and the payoff vector, the utility, for each agent in the game, instead of devising a two-stage algorithm, one to calculate the rate, and another to do the association, as is typically done.

In the remainder of the paper, we describe the studied system model. Then, we provide details about the proposed approach and exhibit its advantages. Next, we show the performance of the blind multi-sided matching compared to the greedy algorithm and distance-based association. Finally, we provide some concluding remarks.

**SYSTEM MODEL**

We consider a multi-layered network with nodes distributed into them as illustrated in Figure 1. In our scenario, the number of layers is 4. However, the proposed solution can be easily extended to a larger number of layers. Ground users belong to the first layer. UAVs belong to the second layer. HAPs are contained in the third layer. Finally, the fourth layer comprises satellites. We refer to nodes in layer \( k \) as *downstream nodes*, and their adjacent upper-layer nodes, in layer \( k + 1 \), as *upstream nodes*. Throughout the paper, We use the symbol \( i \) to denote a downstream node, and the symbol \( j \) to denote an upstream one. As we move up across layers, and consider the communication with the next upper layer, a node, previously considered as an upstream agent, becomes a downstream one.

We assume an uplink communication where UAVs and HAPs act as relays that retransmit data traffic to the satellites. Each UAV communicates both with the users and the HAPs through the air-to-ground and air-to-air channels. Similarly, the HAPs interact with the UAVs and the satellites via air-to-air and air-to-space channels. To communicate with the space tier, a user first sends its data to a UAV, which redirects the traffic to one of the HAPs, and then the HAP transfers the traffic to a selected satellite.

Limiting communication to be hierarchical or only between adjacent layers is not a restrictive assumption. It is possible, for example, to define only three layers: Ground, air, and space layers. Where the air layer encompasses the UAVs and the HAPs links to make it possible for capable users to communicate directly with the HAP and bypass the UAV link, if this is beneficial. It is also possible to define associations involving any number of agents, for example, allowing user-HAP-satellite and user-satellite links. While all these generalizations are possible, the hierarchical framework is adopted here to later present the matching market simply and clearly.
We adopt the ground-to-air, air-to-air and space-to-air channel models described in [5], and assume that nodes belonging to the same layer transmit over the same frequency. Moreover, for simplicity, the 3D positions of the flying nodes and the ground users remain unchanged during communication transmissions. Additionally, we suppose that each downstream node can be associated with, at most, one upstream node, whereas an upstream node \( j \) can serve a group of downstream agents with a maximum quota \( q_j \). In other words, a downstream agent can only associate with a single agent in the adjacent upper layer, while upstream agents can associate with many agents in the layer below them, up to a quota.

The end-to-end data rate from a ground user to the space tier is given by the minimum rate of the relaying links. Indeed, the performance of the communication between the ground tier and the space tier depends on the link that experiences the lowest data rate performance. This link represents the bottleneck in the relaying system, thereby impacting the overall performance.

Our objective is to maximize the sum of end-to-end data rates. This means we need to select which associations are to be made among upstream and downstream agents. Hence, the optimization is over the association variables between the adjacent layers for all agents in all layers. The optimization is constrained by the requirement that the number of associated downstream users does not exceed the quota of the upstream nodes. Due to the integer nature of the association variables and the quota constraint, the underlying optimization problem is a challenging one. To circumvent this difficulty, we formulate our optimization problem within the framework of matching theory and devise a simple algorithm to solve it in the next section.

A Multi-sided Matching Market

In this section, we formulate the studied problem as a multi-sided matching game. Then, we describe the algorithm to maximize the sum of the end-to-end rate and achieve equilibrium.

A Multi-sided matching game

A multi-sided market is defined by \( K \) sectors. In our case, \( K = 4 \), is also the number of layers. Define a basic coalition to contain exactly one agent from each of the \( K \) sectors.

The value of the basic coalition equals the sum of the valuation of its building layers: the user-UAV valuation, plus the UAV-HAP valuation, and the HAP-satellite valuation. The final value of the basic coalition is only accrued after the assignment of all layers is made. This valuation hierarchy follows the chain structure of [13] and guarantees the non-emptiness of the core of our game. As mentioned in the system model, this chain structure is not restrictive but is simpler to present our market.

It is possible to assign more than one downstream agent to a single upstream agent, i.e., we have a multi-sided many-to-one matching game. A UAV may accommodate many users, up to its quota, while a HAP may accommodate many UAVs and a satellite may accommodate many HAPs according to its total quota. We will call an assignment consistent if a single user is only assigned once, and a multi-agent is not assigned more than its quota, otherwise it is inconsistent. As a consequence, a matching, for all agents in the market, is a set of basic coalitions with a consistent assignment across all layers. In Fig. 2, we show an example of consistent and inconsistent matchings.

There exists a \( K \)-dimensional valuation matrix that assigns a value, rate, to each basic coalition. This valuation matrix, along with the set of agents of the different sectors, defines the resulting cooperative game. The outcome of the game is a matching of agents in the different layers supported by a set of imputations: agents’ payoff vectors that are efficient, i.e., attaining value. The payoff vectors are the agents’ share of the value, the rate, which is described, for our scenario, as follows:

- The value of a pair user-UAV is given by the rate of the user with respect to the UAV.
- The value of a pair UAV-HAP is given by the minimum of two values: the sum-rate of users the UAV can accommodate, and the UAV-HAP rate.
- Similarly, the value of a HAP-satellite link is the minimum between the sum of the rates of the UAVs the HAP can accommodate and the HAP-satellite rate.
- Finally, the value of a satellite is the sum of the utilities of its served HAPs.

In practice, the end-to-end data rate in a SAGIN is limited by the ground-to-air link. In general, the ground-to-air transmissions experience the lowest performance due to the existence of no line of sight links and the low transmit power of the users. In such cases, the sum of the end-to-end rates is reduced to the sum of the ground users’ rates. Also, the value of a pair UAV-HAP or HAP-satellite, is given by the sum-rate of the ground users they can accommodate.

Due to the chain structure of the market, we can equally focus on the adjacent layers’ valuation matrices instead of the full \( K \)-dimensional matrix. Because each layer-to-layer interaction involves a many-to-one assignment, one may think of upstream agent \( j \) as having many copies, one for each downstream agent. Hence, agent \( j \) has a valuation for each player \( i \) in the downstream. The goal is to choose the as-
assignment variables so that the resulting value is maximized while maintaining consistency: $i$ users may only be assigned once while $j$ users’ assignments may not exceed their quota. The total value of the matching will equal the sum across the different layers. It is consistent by construction. A matching is optimal if it attains maximum value.

However, optimality is not the only metric to be considered for any successful matching market. Stability is another key performance metric. An algorithm may yield a close to an optimal result, but without stability, the matching is not durable. Markets with many sectors introduce challenges to defining stability due to the multi-sided nature of the market. We refer the interested reader to [10], [14] for more details on the topic. However, and to keep our presentation simple, the notion of pairwise stability, a metric for characterizing the stability of two-sided markets, is still useful here due to two main reasons: The chain valuation structure and the fact that the value of each pair of agents is the same across the different layers, i.e., the minimum rate constraining the link. We are particularly interested in a specific notion of stability called $\epsilon$-stability defined between two agents on the opposite side of the market for two given layers [9]: A matching between two adjacent layers is $\epsilon$-stable if all matched agents attain their value and no $\epsilon$-improvement to two agents’ utility is possible.

Our modeling thus far proved fruitful: We formulated the SAGIN association problem as a multi-sided matching game with a non-empty core. We have an idea of what it means to have an optimal and stable matching, but a question remains as to how to achieve it? We address this next.

A multi-sided matching algorithm

A number of works in the multi-sided assignment literature highlight conditions for non-emptiness of the core, e.g., [10], [13], [15], however very few works construct algorithms to reach them. In our work, we make use of the BLind Matching Algorithm (BLMA) proposed in [9] as a negotiation mechanism between adjacent layers to reach an efficient matching. BLMA is repeatedly applied to the successive layers by exploiting the chain valuation structure. The overall algorithm will be referred to as a Multi-Sided Algorithm (MSA). BLMA uses a simple aspiration learning dynamic. Agents maintain aspiration levels, rates they currently have or have acquired in the past. Agents start out looking for a small improvement, $\epsilon$, over their current aspiration levels. They randomly meet agents upstream or downstream. If both agents can achieve at least this $\epsilon$-improvement, they are said to be agreeable. Hence they match and increase their aspiration levels to sum up to the total value that their pair can generate. Otherwise, if it is not possible for the pair to simultaneously improve their aspiration levels, and if they are already single, then they know they need to reduce such aspirations. The reduction is made by another small number $0 < \delta < \epsilon$. This randomized and simple dynamic can be shown to produce an optimal $\epsilon$-pairwise stable matching.

Fig. 3 presents the MSA when implemented between two adjacent layers. Suppose each node initializes its aspiration level at some random value. Then, when an activated downstream node $i$ encounters an activated upstream node $j$, nodes $i$ and $j$ check to see if they can attain at least a small improvement over their current aspirations. If they are agreeable, and the quota of node $j$ has not been reached yet, node $i$ disconnects from any previous association and associates with
upstream node \( j \).

Otherwise, if node \( j \)'s quota is reached, aerial platform \( j \) checks if the downstream node \( i \)'s utility is more agreeable, better, than one of its served nodes. If so, the aerial platform disconnects the less preferred agent and associates with node \( i \). Furthermore, once the two nodes are associated, they update their aspiration level to sum up to their achievable rate. In case of disagreement, \( i \) reduces its current aspiration level by \( \delta \), if it is single. Moreover, following disagreement, node \( j \) also reduces its \( i \)-th aspiration level by \( \delta \). This process is repeated until all quotas are reached, or all nodes in layer \( k \) are connected.

The main idea behind this multi-sided matching algorithm is to successively connect pairs while respecting their minimum requirements (i.e., aspiration levels). A pair \((i, j)\) disconnects only to build another pair with improved utilities. At the same time, single downstream nodes and upstream agents decrease their aspiration levels to improve their chances of association in the next iterations.

The multi-sided algorithm is guaranteed to achieve the best sum-rate per adjacent layers. It also ensures that the number of associated nodes is maximized. From a computational performance perspective, an active node has only to assess agreeability. Unlike the deferred acceptance algorithm where agents are required to order their utilities with respect to all agents in the opposite set, the MSA checks agreeability only. Moreover, it does not require a large amount of information exchange between pairs. Each agent has only to assess agreeability with respect to the target node in the adjacent layer.

## Performance Evaluation

### Simulation setup

We consider a \( 1 \times 1 \text{ km}^2 \) area where 30 ground devices are randomly scattered. The transmit power of each device is 1 Watt. We assume 8 UAVs that hover at 100m of altitude. In order to transfer the data, UAVs communicate with 3 HAPs with a power of 3 Watt. The HAPs are assumed at an altitude of 17km. They communicate with two satellites at an orbit height of 700km. The transmit power of the HAPs is set to 10 Watt. We also assume that the HAPs antennas' gain is 45 dbi, and the noise spectral density is \(-169 \text{ dbm/Hz}\). To model the ground-to-air channel, we assume a suburban environment and we consider the same parameter values in \([5]\). Ground-to-air, air-to-air, and air-to-space channels are supposed to operate over different frequencies; 2.5 GHz, 5 GHz and 3 GHz for users, UAVs, and HAPs respectively. The communication bandwidth is 10 MHz for each node. We also assume the same quota of 6 for all UAVs, 3 for HAPs, and 2 for satellites.

Fig. 4 plots the global end-to-end rate versus the number of iterations. As depicted in the figure, the MSA approach outperforms both greedy and distance-based association schemes. In fact, the greedy approach selects the best pair of nodes at each iteration. Once the nodes are associated, their association is never revised. Contrarily, the MSA allows a pair of nodes to disconnect and connect with other nodes whenever an \( \epsilon \)-improvement is possible. This process significantly improves the end-to-end rate. Furthermore, while the association based on the distance can be seen as a decentralized approach, it
achieves the worst performance. This is mainly due to the fact that some downstream nodes may remain unconnected due to the high-density regions around their closest upstream node.

In Fig. 4(b), we plot the final association between nodes in the four layers after the MSA convergence. As it can be seen from the figure, the quota of upstream nodes is respected. We can also notice that all ground users are connected, through relays in intermediate layers, to the space tier. This is because, for any adjacent layers, the sum of quotas of agents in the upstream layer is larger than the number of downstream nodes.

In Fig. 4(c), we show the performance of the studied approach for an increasing size of the network. The figure plots the final sum end-to-end rate value against the number of users. As shown in the figure, the MSA always outperforms greedy and closest node associations. In fact, the end-to-end rate increases with the number of devices for both greedy and the MSA algorithms until the quotas of UAVs are reached. However, this value remains constant for the distance-based association. This is due to the high-density of the users around some UAVs. As a consequence, when the number of users increases and the quotas of UAVs remain constant, including additional devices does not necessarily improve the overall performance when the distance-based association is adopted.

**CONCLUSION**

In this paper, we studied the problem of multi-tier association in space-air-ground integrated networks. The multi-layer association is formulated as a multi-sided many-to-one matching game. To ensure stable associations across layers and improve the sum of end-to-end rate, we adopted a fully distributed, asynchronous and low-computational algorithm, referred to as the MSA. Our simulation results showed that significant performance is achieved when compared with the greedy algorithm and distance-based association.

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