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Enabling Wireless-Powered IoT Through Incentive-Based UAV Swarm Orchestration

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ABSTRACT The rapidly growing demand for vast numbers of Internet of Things (IoT), in both urban and rural areas, necessitates their ceaseless and automatic energy supply. This is particularly vital in cases where the IoT sensors are deployed in distant or dangerous locations outside human reach. In this direction, unmanned aerial vehicles (UAVs) with wireless power transfer (WPT) capabilities can address this issue, due to their flexible deployment. To this end, we devise an architecture in which a UAV swarm covers the energy demand of an IoT network, while concurrently, the UAVs fulfil their energy needs through a charging station (CS) infrastructure. A practical energy model is considered, which takes into account the UAVs' battery level, energy consumption due to transition to different locations, hovering, and WPT. Also, to capture the UAV-CS interaction, an economic model is introduced. The UAVs aim to maximize their profit by transferring energy to the IoT, while the CSs aim to maximize their profit by recharging the UAVs. To ensure a profit-wise stable CS-UAV association, while providing energy coverage to the IoT, we formulate a many-to-one matching game. Due to inter-dependencies between UAVs' utilities, i.e., *externalities*, a matching algorithm with two-sided exchange-stability is proposed. To further evaluate the considered system, we design an optimization scheme which performs the UAV-CS assignment towards maximizing the energy coverage of the IDs. Numerical results showcase the matching algorithm's ability to provide near-optimal energy coverage to the IDs, while balancing fairness among the competing agents' profit, compared to the optimization scheme.

INDEX TERMS Internet of Things, UAV swarm, stable matching with externalities, charging stations, wireless power transfer.

I. INTRODUCTION

As a key enabler of smart cities and digital societies, Internet of Things (IoT) networks are already playing a vital role by sensing the physical environment through a massive number of sensor nodes, which are expected to surpass 5 billion by 2028 [1]. Nevertheless, a main issue with the maintainability of IoT networks is energy management, since battery depletion is often the cause of the system's failure [2]. Considering this issue, the obvious solution to replace the failing nodes' batteries is often impractical, especially when they are located in unapproachable areas, such as dams, bridges, or rotating machinery, where human intervention is costly or even dangerous. In this direction, energy harvesting (EH) from ambient sources has been examined for the extension of IoT devices' (IDs) lifetime, however, in most cases, the amount of harvested energy is low and unforeseeable. To this end, new charging methods should be proposed to allow ubiquitous monitoring through randomly deployed sensors, especially when they are located in inaccessible environments.

A novel charging technique that has emerged over the last few years is through wireless power transfer (WPT) in which the sensor nodes harvest energy from radio frequency (RF) signals in a perpetual and cost-effective manner [3], [4]. The advantage of this technology is twofold: i) RF charging leads to "greener" networks, since battery replacements are restricted, and ii) it removes part of the uncertainty, concerning the amount of harvested energy, as opposed to other EH methods such as solar charging [5], [6]. In this way, a source transmits a directive energy beacon signal, so that nearby IDs can harness it for charging. However, to ensure the quality of the WPT operation, the wireless links need to be extremely reliable, ideally with a strong line-of-sight (LoS) component, which is quite difficult, especially when the distance between the source and the destination is large and the WPT system's infrastructure is static [3]. Therefore, it is vital to have the ability to deploy network components in a flexible manner to increase the effectiveness of the WPT schemes, ergo, the overall system's performance.

Considering the need of flexible networking, unmanned aerial vehicles (UAVs) are envisioned as a significant part of future IoT networks due to their ability to offer wireless links with favorable characteristics in an extremely adaptive manner [7], [8], [9], [10] and by optimizing their trajectory their energy efficiency and performance can be greatly increased [11], [12], [13]. Specifically, many relevant studies have shown that UAVs constitute a viable solution for battery recharging, particularly in hard-to-reach areas, since they can be used as dedicated energy transmitters that can be deployed when necessary [14], [15], [16], [17]. Therefore, by taking into account the advancements of UAV-assisted networks, i.e., *aerial networks*, UAV-assisted WPT has emerged as a novel paradigm for delivering energy for recharging purposes [18], [19].

A. STATE-OF-THE-ART

The remote charging capabilities of aerial WPT networks has been well documented in recent studies. Specifically, [20] showed the feasibility of utilizing UAVs to power out-of-grid sensors through experiments, while the authors of [21] proposed a similar scenario for the case where the sensors are deployed below a bridge at hard-to-reach positions. Additionally, in [22], a UAV-assisted WPT system was proposed, where the UAV transmits energy to device-to-device pairs in order to increase their average throughput. Nevertheless, it should be mentioned that the effective utilization of UAVs depends on the remaining energy in the UAVs' battery [8], [10]. In this direction, by taking into consideration the limited UAV energy, the authors in [23] optimized a UAV-assisted WPT system by minimizing its energy consumption while taking into account the users' QoS requirements, while the authors in [24] proposed a resource management method of a UAV-assisted WPT system based on deep Q-learning. Moreover, in [25], two sensor charging strategies of a UAV-assisted WPT system named static charging time allocation (SCTA) and optimal charging time allocation (OCTA) were presented and the suitability of OCTA was demonstrated, especially at higher transmitted power levels. In [26], the authors examined a dynamic matching over multiple periods to pair UAVs with IDs, while [27] proposes a similar two-stage strategy that first locates the IDs and then charges them.

On the other hand, the utilization of specialized charging stations (CSs) with multiple UAV charging docks was proposed in [28] to address the recharging issue of UAV swarms. CSs are deployed in strategic locations to minimize the distance UAVs have to travel before starting the WPT process, thus enabling a bigger percentage of the UAVs' batteries to be allocated for WPT purposes [29]. The charging scheduling problem, as well as the energy trading between UAVs and CSs has been identified in various works [30], [31]. In [30], the optimal charging strategy was examined, whereas in [31], a blockchain-based framework for secure and reliable energy trading between UAVs and CSs was established.

B. MOTIVATION AND CONTRIBUTION

Even though the aforementioned works provided useful insights into UAV-assisted WPT systems, a complete solution for a sustainable UAV network that takes into account the UAV recharging process is still missing from the current state-of-the-art. It is also evident that the large-scale IoT deployments of the future compel the investigation of i) autonomous UAV swarm to handle the complications of the ID charging effectively, and ii) CSs to satisfy the UAV energy needs. Additionally, considering the fluctuating ID energy demands, the UAVs have to be orchestrated regularly in order to be assigned in an appropriate serving area, while being in a safe distance from a CS. At the same time, taking into account the fact that UAVs and CSs may belong to different operators with conflicting objectives in terms of profit, the individual incentive of each operator should be considered, to conduct the UAV assignment with fairness to all involved parties.

To this end, incentive-based algorithms should be designed to provide a mutually accepted solution for every operator based on profit. In order to tackle the problem of assigning resources appropriately with the goal to increase the prosperity of all operators, matching theory is a powerful tool to study the formation of mutually beneficial relations among different types of rational and selfish agents. In this case, the interplay between the CS and UAV operators can effectively be modeled through a matching theoretic approach.

As such, in this paper, we jointly study the profit of both the UAV and the CS operators. The economic model that captures this interaction is formulated as a many-to-one

TABLE 1. List of symbols and notations.

Notation list					
$\mathcal{U}$	UAV set	U	Number of UAVs	u	UAV identification index
$\mathcal{C}$	CS set	C	Number of CSs	c	CS identification index
$\mathcal{N}$	ID set	N	Number of IDs	n	ID identification index
E_u	Initial UAV energy	$E^{\mathrm{o}}_{u,c}$	Overall UAV energy consumption during ID charging	$E^{\mathrm{t}}_{u,c}$	Energy consumption for UAV transitions
H	UAV height	$E^{\mathrm{p}}_{u,c}$	Energy consumption for WPT during ID charging	E^{r}	Energy consumption for UAV relocation
G	UAV antenna gain	E^{h}_{u}	Energy consumption for hovering during ID charging	θ	Antenna aperture
α	Path loss exponent	c_0	Path loss coefficient	q_c	CS quota
ν	UAV velocity	P^{v}	UAV flying power consumption	$d_{u,c}$	Distance between u and c
$\mathcal{N}_c$	Set of IDs in cell c	N_c	Number of IDs in cell c	P^{tx}	UAV transmit power
w_1	Energy cost for UAV	w_2	Energy cost for CS	p	Energy cost for ID
λ	ID intensity	r	Transmit to hover power consumption ratio	E_n	Energy demand for ID n
$E^{\max}_n$	Max energy need of ID n	$E^{\mathrm{w}}_{u,c}$	Energy harvested by the IDs in cell c	t	Unit of time

matching game. Moreover, we formulate and optimally solve an optimization problem which aims to maximize the energy coverage of the IDs, i.e., the ratio of harvested energy by the IDs to their energy demand. The main contributions of this work are summarized below:

- We propose a comprehensive framework for the WPT charging problem where a UAV swarm profits from transferring energy to the IDs, while CSs profit from charging the UAVs.
- A practical energy consumption model for the UAVs is considered, based on their battery capacity, the energy consumption due to multiple transitions, the relocation back to the CS, hovering and WPT for charging the IDs. Based on this model, we define the utilities of the UAV and CS operators, in terms of their achievable profit.
- Using the utilities, we design a many-to-one matching game aiming to assign the UAVs into cells around the CSs. The matching algorithm takes into account the inter-dependencies and peer-effects among the utilities of the operators, thus the concept of matching game with externalities is adopted. The existence of a two-sided stable matching is proved, implying that a stable solution exists. This way, the underlying goal of maximizing the energy coverage of the deployed IoT network is achieved through incentive-based association between all agents.
- To further evaluate the considered system, we design an optimization scheme which performs a UAV-CS assignment with the aim to maximize the energy coverage of the IDs. By applying proper algebraic manipulations, the corresponding problem is transformed into a mixed integer linear programming problem and solved optimally.
- Simulation results verify the near-optimal performance, in terms of energy coverage, of the proposed matching game, while exhibiting higher fairness among the operators' profits compared with the proposed optimization scheme. Additionally, we provide various insights on the UAVs' profit and utilization percentage.

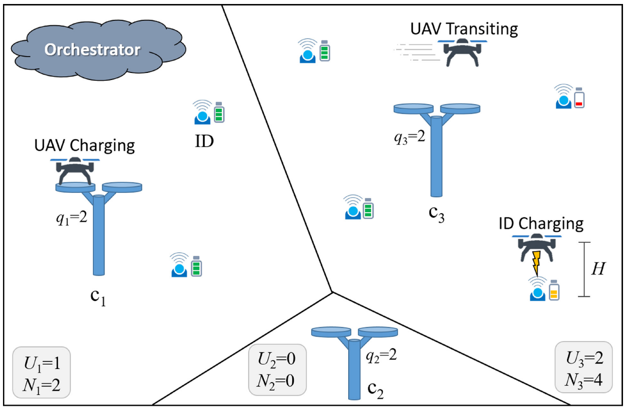

FIGURE 1. Illustrative example of the network entities.

C. STRUCTURE

The rest of the paper is organized as follows: Section II describes the system model in detail. Section III presents the stable matching theory analysis regarding the allocation of UAVs to the suitable CSs. In Section IV, a scheme is designed through an optimization framework aiming to maximize the energy coverage of the IDs. Finally, Section V includes the simulation results and provides useful insights derived from the comparison among the different scenarios, while Section VI concludes the paper.

II. SYSTEM MODEL

In this section, we introduce the system model of our work. First, we discuss the network topology and the entities that constitute the proposed architecture. Then, we provide the energy model for the IDs and the UAVs and, finally, we provide the economic model that determines the profit of the UAV and CS operators. The notation used in the system model is summarized in Table 1.

A. ENTITIES

We examine a large-scale wireless network with IDs served by UAVs, i.e., the UAVs are charging the IDs through far-field WPT. Additionally, to cover the energy requirements of the UAVs, a set of CSs is also distributed on the plane, while a centralized system orchestrates the UAV-CS association to guarantee a context-aware and safe operation. More specifically, the following types of entities are involved in the operation:

- Unmanned Aerial Vehicles (UAVs): We consider the set $\mathcal{U}$, consisting of $U = |\mathcal{U}|$ UAVs, where $|\cdot|$ denotes the cardinality of a set. The purpose of UAV u is to be assigned by the orchestrator to a cell and recharge the IDs of that cell through WPT. Compared to static infrastructure, UAVs have the additional advantage of being able to dynamically relocate and hover at a height H over specific IDs. In this direction, we utilize rotary-wing UAVs to ensure their ability to hover. Moreover, each UAV is powered through a limited capacity battery that needs to be recharged during its operation. To guarantee a safe and autonomous UAV operation, we employ CSs that recharge the UAVs whenever their battery is nearly depleted. The UAVs are required to be assigned and operate in the vicinity of these stations to avoid power outages.
- Charging stations (CSs): We assume the set $\mathcal{C}$ of C CSs, responsible for the UAV-charging that are uniformly distributed, while their positions define a Voronoi tessellation. The c-th CS has the capacity to charge q_c UAVs simultaneously. To that end, we assume that at most q_c UAVs are associated to the c-th CS. It is assumed that $U \leq \sum_{c\in\mathcal{C}} q_c$, meaning that there is always a charging pad for every UAV. However, when $U = \sum_{c\in\mathcal{C}} q_c$ holds, any additional UAV attempting to deploy within the service area would be blocked by the CS operator due to safety concerns.
- IoT devices (IDs): We consider a set $\mathcal{N}$ of IDs lying inside a bounded set $A = [-L, L]^2 \subset \mathbb{R}^2$. The locations of the IDs are defined by a homogeneous stationary Poisson point process (PPP) Φ with intensity λ. By clustering the IDs based on the CS cell that they belong to, we define the sub-set $\mathcal{N}_c \subseteq \mathcal{N}$, $\forall c \in \mathcal{C}$, consisting of $N_c = \lambda v_2(A_c)$ IDs on average in the c-th CS cell, where $v_2(A_c)$ denotes the Lebesgue measure of dimension 2 of set $A_c \subseteq A$. Due to the homogeneity of stationary PPPs, each sub-set $\mathcal{N}_c$ defines a homogeneous PPP with the same intensity λ, given that the sets of IDs in different cells are non overlapping, i.e., $\mathcal{N}_i \cap \mathcal{N}_j = \emptyset$, $\forall i \neq j,\ i, j \in \mathcal{C}$.

B. ENERGY MODEL

1) UAV ENERGY SPECIFICATIONS

The UAVs are equipped with a battery of limited capacity and they are recharged by their associated CS. As aforementioned, the c-th CS possesses q_c charging pads, providing simultaneous UAV charging, while allowing for an uneven UAV distribution. Moreover, we assume that the initial battery energy of the u-th UAV is E_u. Therefore, at any point during the u-th UAV operation at the c-th CS, the overall energy consumption should not exceed the available energy of the UAV. Hence, it should hold that

$$E^{\mathrm{r}}_{u,c} + E^{\mathrm{t}}_{u,c} + E^{\mathrm{o}}_{u,c} \leq E_u, \quad \forall u \in \mathcal{U},\ \forall c \in \mathcal{C}, \tag{1}$$

where the left-hand-side of (1) is defined by the following three terms:

- Relocation: $E^{\mathrm{r}}_{u,c}$ is the energy required for the relocation of UAV u between its initial position and the location of CS c. This is an energy cost applied only after a UAV-CS assignment and it is given by
$$E^{\mathrm{r}}_{u,c} = \frac{d_{u,c} P^{\mathrm{v}}}{v}, \quad \forall u \in \mathcal{U},\ \forall c \in \mathcal{C}, \tag{2}$$
where $d_{u,c}$ is the distance between the initial UAV position and its assigned CS, v is the UAV velocity to reach the location, and P^{v} is the power consumption while the UAV flies with this velocity.
- Transitions: $E^{\mathrm{t}}_{u,c}$ denotes the energy cost for all the transitions of the u-th UAV between the IDs in CS c, while charging them. Given N_c IDs and the set of $\mathcal{U}_c$ UAVs assigned in the c-th cell with $|\mathcal{U}_c| \in \{1, \dots, q_c\}$, there are on average $N_c/|\mathcal{U}_c|$ transitions for each UAV, plus one transition for returning to the CS for the upcoming charging of its battery, i.e., in total $(N_c/|\mathcal{U}_c| + 1)$ transitions. Next, similar to the relocation energy $E^{\mathrm{r}}_{u,c}$, the average UAV energy cost $\bar{\epsilon}$ for each transition from one ID to its nearest one is calculated by considering the distance between them and the power consumption P^{v} while the UAV flies with velocity v. As aforementioned, each sub-set $\mathcal{N}_c$ defines a homogeneous PPP with intensity λ. Hence, the expected value of the distance between two neighboring IDs is given by $1/2\sqrt{\lambda}$ [16]. Therefore, the energy required for the transitions of the u-th UAV within the c-th cell, is given by
$$E^{\mathrm{t}}_{u,c} = \bar{\epsilon}\left(\frac{N_c}{|\mathcal{U}_c|} + 1\right), \quad \forall u \in \mathcal{U},\ \forall c \in \mathcal{C}, \tag{3}$$
where $\bar{\epsilon} = P^{\mathrm{v}}/2v\sqrt{\lambda}$.
- ID charging: $E^{\mathrm{o}}_{u,c}$ is given as
$$E^{\mathrm{o}}_{u,c} = E^{\mathrm{p}}_{u,c} + E^{\mathrm{h}}_{u}, \quad \forall u \in \mathcal{U},\ \forall c \in \mathcal{C}, \tag{4}$$
and represents the overall energy cost for the ID charging of u-th UAV to the IDs in cell c. It should be noted that during the ID charging, a UAV is consuming energy both for WPT and for hovering above the ID, denoted as $E^{\mathrm{p}}_{u,c}$ and E^{h}_{u}, respectively. Specifically, the hovering energy can be written as
$$E^{\mathrm{h}}_{u} = tP^{\mathrm{h}}, \tag{5}$$
where P^{h} is the power consumption dedicated for hovering and t denotes the unit of time. Accordingly, $E^{\mathrm{p}}_{u,c}$ can be written as
$$E^{\mathrm{p}}_{u,c} = tP^{\mathrm{tx}}, \tag{6}$$
where P^{tx} is the transmit power of the UAV. It is straightforward to verify that
$$E^{\mathrm{h}}_{u} = \frac{E^{\mathrm{p}}_{u,c}}{r}, \tag{7}$$

where $r = {}^{P^{\text{tx}}}/{}_{P^{\text{h}}}$, which, finally, yields

$$E^{\text{o}}_{u,c} = \frac{r+1}{r} E^{\text{p}}_{u,c}. \tag{8}$$

2) WPT ENERGY SPECIFICATIONS

The energy need of the n-th ID is a random variable denoted as E_n, following the uniform distribution in $[0, E_n^{\max}]$, where $E_n^{\max}$ is the maximum energy need of the n-th ID. Furthermore, at any time, the central orchestrator is aware of each ID's energy demand. Therefore, to measure the amount of energy harvested by the IDs of cell c, we need to take into account $E^{\text{p}}_{u,c}$, i.e., the maximum available energy that the UAVs in $\mathcal{U}_c$ are allowed to provide for ID charging. Additionally, it should be considered that the IDs are recharged by the UAVs through WPT with their EH circuit having an RF-to-DC conversion efficiency η and that the transmitted UAV power P^{tx} for ID charging is subject to path loss. Hence, considering LoS links between UAVs and IDs, we assume that the UAVs are equipped with a directional antenna with gain $G = c_0 \frac{29000}{\theta^2} H^{-\alpha}$, where α is the path loss exponent, c_0 is the path loss coefficient, and θ is the antenna aperture. Thus, by substituting (8) in (1) and considering that $E^{\text{w}}_{u,c} = \eta G E^{\text{p}}_{u,c}$, the amount of RF energy harvested by the IDs from UAV u in cell c, denoted by $E^{\text{w}}_{u,c}$, is obtained as

$$E^{\text{w}}_{u,c} = \min\left\{ \beta\left(E_u - E^{\text{t}}_{u,c} - E^{\text{r}}_{u,c}\right), \sum_{n \in \mathcal{N}_c} \frac{E_n}{|\mathcal{U}_c|} \right\}, \tag{9}$$

where we set $\beta \triangleq \frac{G\eta r}{r+1}$. It is evident from (9) that in case of $|\mathcal{U}_c| > 1$, the energy demand in the c-th cell is shared among the assigned UAVs.

C. ECONOMIC MODEL

In our model, we assume that there are three kinds of operators:

1) ID OPERATOR

The ID operator is responsible for the deployment of the IDs in specified areas that are difficult or dangerous to reach, so human intervention is in general undesirable. After the initial deployment, the ID operator depends on UAVs for the ID charging and reimburses the UAV operators p currency units per mWh for the transferred energy at its IDs. Through this interaction, the ID operator aims to meet the energy demands of the IDs towards providing increased energy coverage.

2) UAV OPERATORS

Each UAV operator owns a single UAV and is responsible for the IDs charging. Its main objective is to increase its profit by transferring as much energy as possible to the IDs, while competing among the other UAV operators for the safest and least expensive, in terms of energy, CS association. In detail, a UAV operator profits p currency units per mWh transferred at the IDs in cell c and compensates the CS owner w_1 currency units per Wh for recharging its battery up to the initial energy level E_u. Therefore, the utility $O^{\text{UAV}}_{u,c}$ of the u-th UAV in the c-th CS, is the profit of u, and it is defined as

$$O^{\text{UAV}}_{u,c} = pE^{\text{w}}_{u,c} - w_1\left(E^{\text{r}}_{u,c} + E^{\text{t}}_{u,c} + E^{\text{o}}_{u,c}\right). \tag{10}$$

3) CS OPERATOR

We consider a single CS operator, which is the owner of all CSs on the plane and is responsible for the UAV charging and informing the central orchestrator about the status of the IDs in its cell. The main objective of the CS operator is to maximize its profit by recharging the UAVs. Specifically, it receives w_1 currency units per Wh, while spending w_2 currency units per Wh for the electricity from the grid. At the same time, the safety of the aerial network is indirectly increased, since the low-battery UAVs, after accounting for the relocation energy cost, are preferred by the CSs. In such way, it is guaranteed that a UAV will be associated with a CS in its reach, eliminating potential failures due to unfavorable associations. Hence, the utility $O^{\text{CS}}_{u,c}$ of the c-th CS when charging the u-th UAV is defined as

$$O^{\text{CS}}_{u,c} = (w_1 - w_2)\left(E^{\text{r}}_{u,c} + E^{\text{t}}_{u,c} + E^{\text{o}}_{u,c}\right). \tag{11}$$

Nevertheless, given that the CS operator is the owner of all CSs, its overall utility O^{CSO} is given by

$$O^{\text{CSO}} = \sum_{c \in \mathcal{C}} \sum_{u \in \mathcal{U}_c} O^{\text{CS}}_{u,c}. \tag{12}$$

To this end, we assume a trusted third-party, namely the central orchestrator, which manages the procedure by defining the UAVs assignment to specific cells. This assignment should take into account the operators' need for profit. Therefore, it is imperative to address the UAV-CS association issue in a fair and profitable way for all participating operators.

III. UAV-CS MATCHING GAME WITH EXTERNALITIES

As discussed in Section II, there is a two-agent competition regarding the UAV-CS association problem. Therefore, it is essential to match every UAV to a CS in a way that satisfies the fairness and profitability for both UAV and CS operators, while aiming towards increased energy coverage of IDs, which benefits the ID operator. In this scenario, the powerful tools of matching theory [32] can be proven effective to obtain a suitable association that guarantees stability, in the sense that agents do not have incentive to change assignments after being matched. Thus, in the following, we introduce the proposed stable matching game formulation.

A. MATCHING GAME WITH EXTERNALITIES

Similar to the students-houses assignment framework provided in [33], we consider a many-to-one matching algorithm that assigns UAVs to CSs, with the latter admitting a quota of q_c UAVs. Hence, each operator prioritizes its preferences based on the utility functions (10) and (12), and the matching algorithm decides an assignment in the most satisfactory way for all parties. Therefore, the network dynamically allocates its resources with the underlying goal of meeting the current requirements in terms of energy provision to the IDs. This framework is suitable for our proposed problem, as it can provide a stable and desirable association among the network entities, while increasing their profit.

It is of paramount importance to highlight that, in opposition to the seminal matching game in [32], our work presents some particularities, rendering the traditional matching game in [32] unsuitable. To be more specific, by observing (10) and (11), it is evident that there are "peer" effects, since there could be conflicting interests among UAVs, given that the utility of a UAV depends on the choices of other UAVs, as there are external effects in every choice. For instance, assigning a UAV u in a CS c with one UAV u' already assigned, potentially changes the utility of u', as the task of IDs charging will be now shared with u, which is evident from (9). Therefore, to tackle the issue of the dynamically changing and inter-dependent utilities, we adopt the framework of matching games with externalities [33]. In what follows, we proceed with the definition of a UAVs-CSs matching.

Definition 1: Given the sets of UAVs $\mathcal{U}$ and CSs $\mathcal{C}$, a matching is a subset $\mu \subseteq \mathcal{U} \times \mathcal{C}$, where $\mathcal{U} \times \mathcal{C}$ is the Cartesian product of $\mathcal{U}$ and $\mathcal{C}$, such that

(i) $|\mu(u)| = 1$, where $\mu(u) = \{c \in \mathcal{C} : (u, c) \in \mu\}$, $\forall u \in \mathcal{U}$.

(ii) $|\mu(c)| = q_c$, where $\mu(c) = \{u \in \mathcal{U} : (u, c) \in \mu\}$, $\forall c \in \mathcal{C}$.

It is noted that the matching μ describes a UAV-CS association such that UAVs are matched to a single CS, while CSs are matched to multiple UAVs. Specifically, the first condition of Definition 1 indicates that each UAV is associated exclusively with one CS. The second condition expresses that CSs do not get associated with more UAVs than they can accommodate, i.e., q_c, on their charging pad(s). Notice that if the number of UAVs in cell c is less than q_c, i.e., $|\mathcal{U}_c| < q_c$, we consider that $\mu(c)$ contains $q_c - |\mathcal{U}_c|$ "holes", represented as virtual UAVs with zero utilities and arbitrary preferences. Due to the externalities, prior to the definition of matching stability, we utilize the concept of swap-matching [33], which is defined below.

Definition 2: A swap matching among the UAV-CS pairs (u, c) and (u', c') is given as

$$\tilde{\mu} = \{\mu \setminus \{(u, c), (u', c')\}\} \cup \{(u, c'), (u', c)\}.$$

Note that the entities directly involved in the swap are the UAVs, u, u' and the CSs, c, c', while all the residual matchings remain unchanged. Note also that one of the UAVs in the given swap may be a "hole". In this manner, the movement of a single UAV to an open available charging pad is enabled.

Definition 3: A matching μ is two-sided exchange stable if there exist no swap-matching $\tilde{\mu}$, i.e., if and only if there does not exist a pair of UAVs (u, u') such that the two following conditions are met

(i) $\forall i \in \{u, u'\}$,
$O^{\text{UAV}}_{i,\tilde{\mu}(i)} \geq O^{\text{UAV}}_{i,\mu(u)}$ and $O^{\text{CSO}}(\tilde{\mu}) \geq O^{\text{CSO}}(\mu)$

(ii) $\exists i \in \{u, u'\}$:
$O^{\text{UAV}}_{i,\tilde{\mu}(i)} > O^{\text{UAV}}_{i,\mu(i)}$ or $O^{\text{CSO}}(\tilde{\mu}) > O^{\text{CSO}}(\mu)$.

Notice here that we slightly abuse the notation by introducing the matching as an argument of O^{CSO}, where the respective UAVs-CSs association is implicit. The above definition states that if two UAVs desire to switch between two CSs (or a single UAV wants to switch with a "hole"), the CS operator must approve the swap, i.e., its overall utility after the swap should not decrease. Moreover, both UAVs' utilities should not decrease, while at least one of the involved entities' utility should increase, which is reflected by (ii) in Definition 3.

B. EXISTENCE OF TWO-SIDED EXCHANGE STABLE MATCHINGS

In this section, we prove the existence of a two-sided exchange stable matching for the UAV-CS matching game. In accordance with [33], we note that each CS can be seen as a "house", and each UAV as a "student". Nonetheless, our investigated system presents some differences from [33], in the sense that we are interested in maximizing the total profit of the CSs, i.e., the profit of the CS operator, and not the individual profits of the CSs. First, we define the potential function $\Phi(\mu)$ for a matching μ, as

$$\Phi(\mu) \triangleq \sum_{c \in \mathcal{C}} \sum_{u \in \mathcal{U}_c} O^{\text{CS}}_{u,c} + \sum_{c \in \mathcal{C}} \sum_{u \in \mathcal{U}_c} O^{\text{UAV}}_{u,c}. \tag{13}$$

It is easy to verify that for any matching $\tilde{\mu}$, which satisfies the conditions (i) and (ii) of Definition 3, it holds $\Phi(\tilde{\mu}) > \Phi(\mu)$. Specifically, by using Definition 2 and applying algebraic manipulations, the difference of the potential functions on the matching μ and $\tilde{\mu}$ is given as

$$\begin{aligned}
&\Phi(\tilde{\mu}) - \Phi(\mu) \\
&\quad = \left(O^{\text{UAV}}_{u,\tilde{\mu}(u)} - O^{\text{UAV}}_{u,\mu(u)}\right) + \left(O^{\text{UAV}}_{u',\tilde{\mu}(u')} - O^{\text{UAV}}_{u',\mu(u')}\right) \\
&\qquad + \left(O^{\text{CS}}_{u',\tilde{\mu}(u')} - O^{\text{CS}}_{u,\mu(u)}\right) + \left(O^{\text{CS}}_{u,\tilde{\mu}(u)} - O^{\text{CS}}_{u',\mu(u')}\right) \\
&\quad = \left(O^{\text{UAV}}_{u,\tilde{\mu}(u)} - O^{\text{UAV}}_{u,\mu(u)}(\mu)\right) + \left(O^{\text{UAV}}_{u',\tilde{\mu}(u')} - O^{\text{UAV}}_{u',\mu(u')}\right) \\
&\qquad + \left(O^{\text{CSO}}(\tilde{\mu}) - O^{\text{CSO}}(\mu)\right) > 0.
\end{aligned} \tag{14}$$

According to [33, Th. 2], all local maxima of $\Phi(\mu)$ are two-sided exchange stable. In (14), it is proven that for an acceptable swap matching $\tilde{\mu}$, $\Phi(\tilde{\mu}) > \Phi(\mu)$ has to hold, and as the number of matches is finite, the global maximum of the potential function must be stable, and therefore, a two-sided exchange stable matching will always exists.

C. PROPOSED ALGORITHM FOR FINDING A STABLE MATCHING

To obtain a stable matching for the UAV-CS matching problem, we propose Algorithm 1. In the beginning of the algorithm, the matching μ is initialized arbitrary. Then, the swap-matching procedure begins until a stable matching μ exists. In order to determine μ, the two conditions of

Algorithm 1: UAV-CS Matching Algorithm

```
Initialize matching μ
while μ is non-stable do
    for u ∈ 𝒰 do
        for c′ ∈ 𝒞 \ {μ(u)} do
            for u′ ∈ μ(c′) do
                μ̃ ←{μ \ {(u, μ(u)), (u′, c′)}} ∪
                    {(u, c′), (u′, μ(u))}
                if Definition 3 (i) & (ii) are met then
                    μ ← μ̃
                end
            end
        end
    end
end
Output: Stable matching μ
```

Definition 3 that indicate whether μ is two-sided exchange stable, should be met. More specifically, we need to examine if two UAVs u and u' that are assigned in different CSs $\mu(u)$ and c', respectively, would prefer to swap with each other. The considered swap will take place if and only if their utility and the CSO's utility are not decreased, while concurrently at least one of the involved entities' utility increases. If these two conditions are met, the swap is beneficial for all players and the matching μ is updated with the new matching $\tilde{\mu}$. Otherwise, the algorithm continues for the next UAV (u, u') pair, until every pair has been examined. Therefore, the matching game terminates, when a satisfactory and stable association between all UAVs and all CSs, i.e., an optimal relocation of the UAVs with respect to their current positions and the cells' energy demand, is obtained, which aims towards increased energy coverage.

It should be noted that this matching holds until the network conditions require an update. Ideally, this should happen after every UAV charging. Then, a new matching procedure initiates to satisfy the current network characteristics.

IV. ENERGY COVERAGE MAXIMIZATION SCHEME

Although the proposed matching game has an underlying goal to provide enhanced energy coverage to the IDs, it does not necessarily guarantees maximized energy coverage. Driven by this consideration, we design a scheme, which inherently focuses on maximizing the overall energy coverage of the IDs. Notice that the aforementioned problem is equivalent to minimizing the total residual energy, i.e., the portion of the IDs' energy demand, which has not been covered by the UAVs. In this direction, we formulate the following optimization problem:

$$\begin{aligned}
\min_{\boldsymbol{A},\boldsymbol{E}^{\mathrm{w}}} \ & \sum_{c=1}^{C} \max\left\{\sum_{n\in\mathcal{N}_c} E_n - \sum_{u=1}^{U} a_{u,c}E^{\mathrm{w}}_{u,c},\ 0\right\} \\
\text{s.t.}\ & \mathrm{C}_1: a_{u,c} \in \{0,1\}, \quad \forall c\in\mathcal{C},\ \forall u\in\mathcal{U}, \\
& \mathrm{C}_2: \sum_{u=1}^{U} a_{u,c} \le q_c, \quad \forall c\in\mathcal{C}, \\
& \mathrm{C}_3: \sum_{c=1}^{C} a_{u,c} \le 1, \quad \forall u\in\mathcal{U}, \\
& \mathrm{C}_4: \frac{E^{\mathrm{w}}_{u,c}}{\beta} + E^{\mathrm{r}}_{u,c} + \bar{\epsilon}\left(\frac{N_c}{\sum_{i=1}^{U} a_{i,c}} + 1\right) \le E_u, \\
& \forall u\in\mathcal{U},\ c\in\mathcal{C},
\end{aligned} \tag{15}$$

where $a_{u,c} \in \{0, 1\}$ is a binary variable indicating whether the u-th UAV is assigned to the c-th CS, i.e., $a_{u,c} = 1$, or not. Also, we define for compactness the matrices $\boldsymbol{A}$ and $\boldsymbol{E}^{\mathrm{w}}$, with their (u, c)-th element being equal to $a_{u,c}$ and $E^{\mathrm{w}}_{u,c}$, respectively. Moreover, C_2 reflects the quota constraint, C_3 implies that each UAV can be assigned to at most one CS, while C_4 indicates that the overall energy consumption cannot exceed the maximum available energy of the UAVs. It is clarified that the problem in (15) is mixed-integer non-linear and non-convex and, thus, it cannot be solved directly without proper transformations.

1) PROPOSED SOLUTION

In what follows, we propose a solution to the problem in (15). First, for any given UAV-CS assignment $\boldsymbol{A}$, an optimal solution occurs when C_4 is satisfied with equality. This is easy to verify, since the function $\max\{\cdot, 0\}$ is decreasing w.r.t. $E^{\mathrm{w}}_{u,c}$, and so is the objective function. This yields

$$E^{\mathrm{w}}_{u,c} = \beta\left(E_u - E^{\mathrm{r}}_{u,c} - \bar{\epsilon}\left(\frac{N_c}{\sum_{i\in\mathcal{U}} a_{i,c}} + 1\right)\right), \ \forall c, u. \tag{16}$$

By substituting (16) in (15), the non-zero argument of the $\max\{\cdot, 0\}$ function can be written $\forall c \in \mathcal{C}$ as

$$\begin{aligned}
f_c(\boldsymbol{A}) \triangleq & \sum_{n\in\mathcal{N}_c} E_n - \beta \sum_{u=1}^{U} a_{u,c}\left(E_u - E^{\mathrm{r}}_{u,c} - \bar{\epsilon}\right) \\
& + \beta \sum_{u=1}^{U} a_{u,c}\left(\frac{\bar{\epsilon}N_c}{\sum_{i=1}^{U} a_{i,c}}\right) \\
= & \sum_{n\in\mathcal{N}_c} E_n - \beta\left(\sum_{u=1}^{U} a_{u,c}\left(E_u - E^{\mathrm{r}}_{u,c} - \bar{\epsilon}\right) - \bar{\epsilon}N_c\right).
\end{aligned} \tag{17}$$

Thus, (15) can be rewritten as

$$\begin{aligned}
\min_{\boldsymbol{A}} \ & \sum_{c=1}^{C} \max\{f_c(\boldsymbol{A}),\ 0\} \\
\text{s.t.}\ & \mathrm{C}_1: a_{u,c} \in \{0,1\}, \quad \forall c\in\mathcal{C},\ \forall u\in\mathcal{U}, \\
& \mathrm{C}_2: \sum_{u=1}^{U} a_{u,c} \le q_c, \quad \forall c\in\mathcal{C}, \\
& \mathrm{C}_3: \sum_{c=1}^{C} a_{u,c} \le 1, \quad \forall u\in\mathcal{U}.
\end{aligned} \tag{18}$$

It is clarified that with the latter transformation the objective function in (18) is convex, since the function $\max\{\cdot, 0\}$

is convex and $f_c(\boldsymbol{A})$ is linear w.r.t. $\boldsymbol{A}$. Moreover, C_2 and C_3 are affine w.r.t. $\boldsymbol{A}$, rendering the problem convex. To this end, we further transform the problem in (18) to its epigraph form equivalent [34], by introducing the auxiliary variable $\boldsymbol{y} = (y_1, \ldots, y_C)$, leading to

$$\begin{aligned} \min_{\boldsymbol{A},\boldsymbol{y}} \quad & \sum_{c=1}^{C} y_c \\ \text{s.t.} \quad & \mathrm{C}_1 : a_{u,c} \in \{0,1\}, \quad \forall c \in \mathcal{C}, \forall u \in \mathcal{U}, \\ & \mathrm{C}_2 : \sum_{u=1}^{U} a_{u,c} \le q_c, \quad \forall c \in \mathcal{C}, \\ & \mathrm{C}_3 : \sum_{c=1}^{C} a_{u,c} \le 1, \quad \forall u \in \mathcal{U}, \\ & \mathrm{C}_4 : y_c \ge f_c(\boldsymbol{A}), \quad y_c \ge 0, \quad \forall c \in \mathcal{C}. \end{aligned} \tag{19}$$

It is obvious that the problem in (19) is a mixed-integer linear problem and, consequently, it can be solved with standard off-the-shelf methods, and guarantee optimality in terms of energy coverage.

By solving problem (19) the UAV-CS assignment matrix $\boldsymbol{A}$ can be obtained, while the delivered energy from the UAVs to the IDs can be retrieved from (16), as

$$E_u^{\mathrm{w}} = \sum_{c=1}^{C} a_{u,c} E_{u,c}^{\mathrm{w}}, \quad \forall u \in \mathcal{U}. \tag{20}$$

However, it should be taken into account that by using the above solution, it may hold $\sum_{u\in\mathcal{U}_c} E_u^{\mathrm{w}} > \sum_{n\in\mathcal{N}_c} E_n$, implying that the UAVs in the c-th cell deliver more energy than it is required by the IDs in the respective cell. The previous case is indifferent for the solution to (19), where optimality still holds. However it may be impractical since the UAVs spend excessive energy. To address this issue, we adopt the following approach. First, we define the set $\mathcal{K}$, which includes all cells to which the UAVs deliver more energy than it is required, i.e.,

$$\mathcal{K} \triangleq \left\{ c \in \mathcal{C} : \sum_{u\in\mathcal{U}_c} E_u^{\mathrm{w}} > \sum_{n\in\mathcal{N}_c} E_n, \quad \forall c \in \mathcal{C} \right\}. \tag{21}$$

Following that, for all UAVs assigned in the c-th cell, i.e., $\forall u \in \mathcal{U}_c$, $c \in \mathcal{K}$, we aim to obtain a new solution $\tilde{E}_u^{\mathrm{w}}$ which satisfies

$$\sum_{u\in\mathcal{U}_c} \tilde{E}_u^{\mathrm{w}} = \sum_{n\in\mathcal{N}_c} E_n, \quad \forall c \in \mathcal{K}, \tag{22}$$

ensuring that the UAVs deliver no more energy than it is required. It is noted that multiple selections of $\tilde{E}_u^{\mathrm{w}}, \forall u \in \mathcal{U}_c$, $c \in \mathcal{K}$, could satisfy the condition in (22). An intuitive and fair strategy is to obtain the nearest solution, $\tilde{E}_u^{\mathrm{w}}$, to the original solution. Hence, we aim to minimize $|\tilde{E}_u^{\mathrm{w}} - E_u^{\mathrm{w}}|$, $\forall u \in \mathcal{U}_c$, subject to (22). Thus, $\forall c \in \mathcal{K}$, we formulate the following least-squares problem

$$\begin{aligned} \min_{\tilde{E}_u^{\mathrm{w}}} \quad & \sum_{u\in\mathcal{U}_c} \left(\tilde{E}_u^{\mathrm{w}} - E_u^{\mathrm{w}}\right)^2 \\ \text{s.t.} \quad & \mathrm{C}_1 : \sum_{u\in\mathcal{U}_c} \tilde{E}_u^{\mathrm{w}} = \sum_{n\in\mathcal{N}_c} E_n, \\ & \mathrm{C}_2 : \tilde{E}_u^{\mathrm{w}} \le E_u^{\mathrm{w}}, \quad \forall u \in \mathcal{U}_c. \end{aligned} \tag{23}$$

It is obvious that the problem in (23) is convex and can be solved by standard convex optimization methods, such as the interior-point method, with complexity of $\mathcal{O}(|\mathcal{U}_c|^3)$, where $|\mathcal{U}_c|$ is the number of optimization variables. For a more efficient solution, problem (23) can be solved by introducing auxiliary variables to the equality constraint C_1, and adopting a similar approach to that outlined in [35, Sec. IV]. The latter method relies on the Karush–Kuhn–Tucker conditions, and it was shown to have a complexity of $\mathcal{O}(|\mathcal{U}_c|^2)$. Either way, (23) outputs the actual delivered energy of the UAVs to the IDs.

V. NUMERICAL AND SIMULATION RESULTS

In this section, we validate the proposed theoretical framework via extensive simulations and provide useful insights on the performance of the UAV deployment by comparing the metrics of interest for the various scenarios. All simulation results were calculated in a Monte Carlo fashion and 2.5×10^5 independent iterations were used. For the performance evaluation, we consider three different techniques: i) the stable matching (SM) that is extensively discussed in Section III, ii) the random matching (RM) that assumes a random UAV-CS association, which serves as the initial matching μ of Algorithm 1 that SM improves through swap-matching, and iii) the energy coverage maximization (ECM) scheme, as discussed in Section IV.

A. SIMULATION SETUP

We consider a 1000 m $\times$ 1000 m area with 5 CSs and 12 UAVs. The CSs have a quota of 4, while the UAVs are randomly deployed and are equipped with a battery with capacity modeled as a uniformly distributed random variable within $[180, 200]$ Wh. The UAV charging height is set to 1 m, which is a realistic choice that ensures efficient RF energy delivery, while maintaining a safe clearance between the UAV and the ID. Additionally, the UAV power consumption figures are carefully derived based on the UAV energy models given in [8], [11]. Moreover, the IDs with energy demands are a subset of the total number of IDs and their number is defined by the Poisson distribution with intensity $\lambda = 6 \times 10^{-5}$. It is noted that the energy demand of each ID is a uniformly distributed random variable within $\left[0, E^{\max}\right]$. The rest of the simulation parameters[1] are listed in Table 2 and retain their respective values, unless specified otherwise.

B. PERFORMANCE EVALUATION AND COMPARISON

In Fig. 2, we illustrate the initial position of one snapshot of a small-scale UAV-CS network to showcase the procedure followed by each association technique. The deployment

1. The chosen values for the energy costs correspond to realistic numbers in euros, but we present them as currency units for the sake of generality.

TABLE 2. Simulation parameters.

Simulation Parameter	Symbol	Value
Simulation Area	A	1000 m $\times$ 1000 m
Number of CSs	C	5
CS Quota	q_c	4
Number of UAVs	U	12
ID intensity	λ	60×10^{-5}
Path loss exponent	α	2.5 (LoS)
Path loss coefficient	c_0	10^{-3}
UAV Transmission power	P^{tx}	37 dBm
UAV Antenna beam width	θ	40^o
Conversion efficiency	η	60%
Initial UAV energy	E_u	$[180, 200]$ Wh
UAV charging height	h	1 m
UAV consumption at 10 m/s	P^{v}	350 Wh
UAV consumption at hover	P^{h}	300 Wh
Energy cost for UAV	w_1	0.01 curr. unit/Wh
Energy cost for CS	w_2	0.001 curr. unit/Wh
Energy cost for ID	p	0.5 curr. unit/mWh

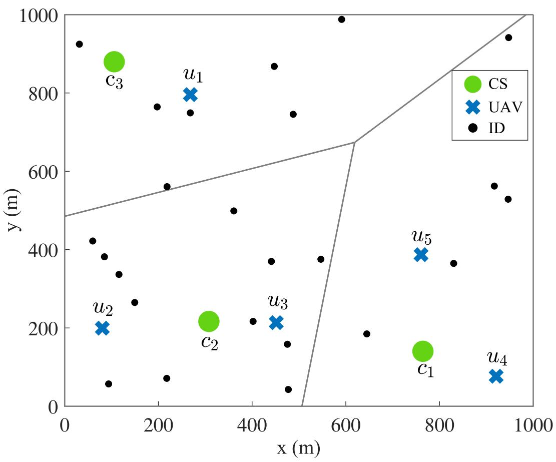

FIGURE 2. Snapshot of an initial network deployment in a 1000 m x 1000 m area with 3 CSs, 5 UAVs, and 24 IDs with maximum energy demand 40 J.

consists of 3 CSs that define 3 cells, 5 randomly positioned UAVs, and 24 IDs with $E^{\max} = 40$ J for each ID. In Table 3, we provide the characteristics and the performance of the snapshot, in which we notice that the energy demand of c_2 is higher, since there are more IDs in its cell that demand energy, i.e., 12 IDs compared to 5 and 7 for c_1 and c_3, respectively. Moreover, in the same table, we provide the UAV association for each technique, namely SM, RM, and ECM, where we can observe that, while RM did not assign any UAVs in the most demanding cell, SM and ECM assigned 3. It is interesting to notice that SM and ECM ended up with the same number of UAVs in each cell. However, since ECM and SM have different goals, the covered demand in each cell is different, i.e., ECM provides an optimal energy coverage, whereas SM provides a mutually acceptable association with near-optimal energy coverage. This can be also verified in Table 4, where the energy coverage of SM is near to ECM.

In the same table, we also provide the mean UAV profit and the CSO profit. Again, it is evident that SM improves significantly the operators' profits compared with RM and

TABLE 3. Snapshot characteristics.

Charging Station		c_1	c_2	c_3
Number of IDs		5	12	7
Energy demand (Wh)		0.03	0.10	0.05
UAVs	SM	u_4	u_1, u_2, u_3	u_5
	RM	u_1, u_2, u_4	-	u_3, u_5
	ECM	u_1	u_2, u_3, u_5	u_4
Cell demand covered (Wh)	SM	0.03	0.099	0.034
	RM	0.03	0	0.05
	ECM	0.03	0.1	0.035

TABLE 4. Snapshot performance.

	SM	**RM**	**ECM**
Energy coverage	90.3%	44.4%	91.6%
Mean UAV profit	14.48	7.11	14.52
CSO profit	8.32	4.43	8.54
Inequality index	0.02	0.29	0.05

it demonstrates a near-optimal performance compared with ECM. Moreover, since each UAV belongs to a different operator, it is important to investigate the fairness of each association method. Gini's index is a measure of the distribution of profit across a population and, thus, suitable for this objective. However, when the ID energy demand is low, it is expected for some UAVs to have negative profit due to charging costs and low revenue from ID charging, resulting in inaccurate Gini index values. To alleviate this burden, we employ Raffinetti's et al. corrected and normalized index [36] defined as

$$\mathcal{G}(\boldsymbol{O}) = \frac{\sum_{i=1}^{U} \sum_{j=1}^{U} \|O_i^{\text{UAV}} - O_j^{\text{UAV}}\|}{2(U-1)(T_a + T_n)}, \tag{24}$$

where $\boldsymbol{O}$ denotes the vector with all UAVs' utilities, while T_a and T_n is the sum of all positive and absolute negative values in $\boldsymbol{O}$, respectively. A value of 0 in (24) indicates perfect fairness, while a value of 1 indicates that the inequality among UAVs is the highest, i.e., few UAVs receive a higher share of profit than the rest. From Table 4, it can be seen that SM presents higher fairness compared to any other methods given that each UAV is assigned to each highest possible preference. This result demonstrates the ability of SM to provide a near-optimal and fairer performance compared to the other methods.

Next, in Fig. 3, we demonstrate the energy coverage versus the maximum ID energy demand $E^{\max}$ for the different considered matching techniques. It is highlighted that all the following results have been averaged in a Monte Carlo fashion. As expected, the ECM showcases the maximum energy coverage, which SM follows closely, while RM presents a degraded performance. It should be recalled that the direct goal of SM is not to maximize the energy coverage, but to provide a mutually acceptable association among UAVs and CSs that benefits all operators in terms of profit. Hence, SM has an indirect goal to provide enhanced energy coverage as the profit depends on the harvested energy by the IDs. As a consequence, it is evident that SM results

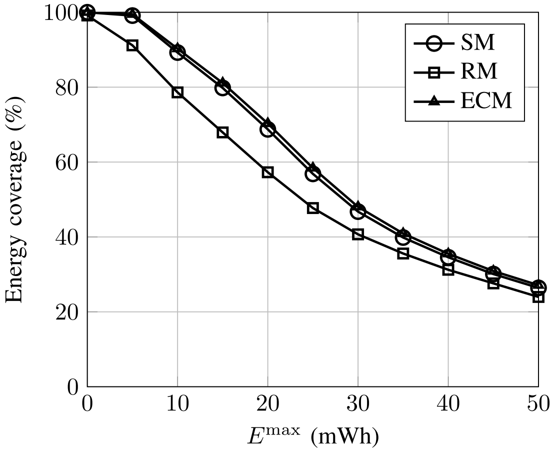

FIGURE 3. Energy coverage vs maximum energy demand per ID.

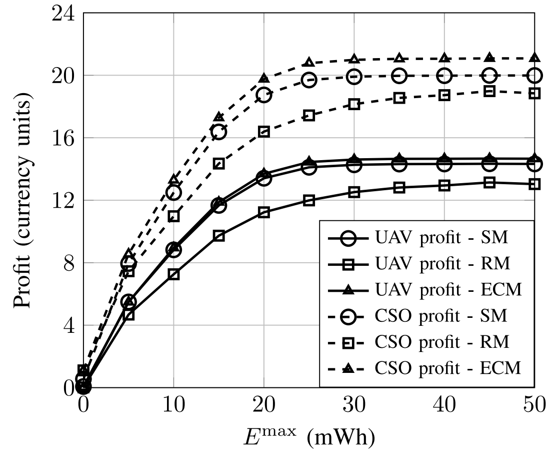

FIGURE 5. CSO and mean UAV operators profit vs maximum energy demand per ID.

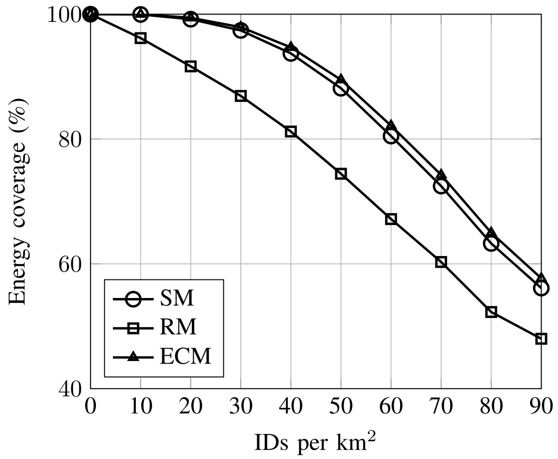

FIGURE 4. Energy coverage vs IDs per km^2.

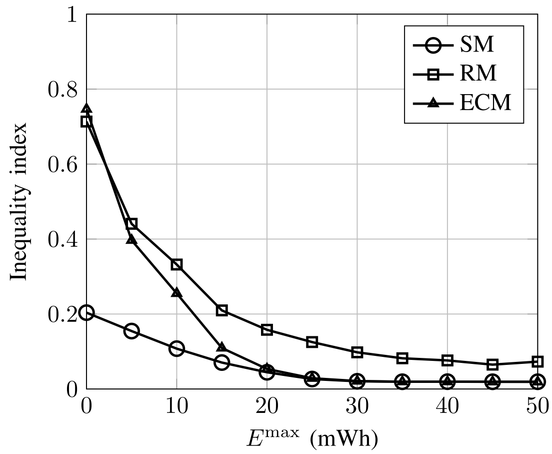

FIGURE 6. Raffinetti normalization of the Gini index of the UAV operators' profits vs maximum energy demand per ID.

in enhanced energy coverage by exhibiting a near-optimal performance. Moreover, we notice that as $E^{\max}$ increases, the energy coverage of all techniques decreases as the available UAV energy is not enough to cover the increasing ID requirements. Obviously, for $E^{\max}$ higher than 30 mWh, the performance of all techniques is almost equivalent, as it is more probable that any association results in UAVs unable to satisfy the high ID energy demands. Similarly, in Fig. 4, we present the energy coverage for different ID densities per km^2, when the $E^{\max}$ is 15 mWh. Again, we notice the near-optimal performance of SM compared to ECM and that the energy coverage of all methods drops as the ID intensity increases, because the cell energy demand increases.

In Fig. 5, we depict the average UAV profit and the total CSO profit for the considered techniques against the $E^{\max}$. First, we notice that as $E^{\max}$ gets higher, the profit of the UAV operators increases, since they serve more IDs and, thus, have more revenue. At the same time, as more energy is spent by the UAVs, their own energy requirements are higher resulting in higher profit of the CSO. The profit of all operators is saturated, though, at approximately 30 mWh, which stems from the fact that as $E^{\max}$ increases, the energy demand in each cell becomes higher than the potential WPT that can be provided by the maximum number of UAVs allowed to serve this cell. Moreover, in line with expectations, both SM and ECM provide higher profits than RM. Additionally, ECM and SM exhibit almost identical mean UAV profit, while the CSO profit is higher in the case of ECM. This can be attributed to the maximum energy coverage that ECM guarantees, which results in higher energy consumption of UAVs. Hence, the CSO may benefit due to extensive charging services to the UAVs.

In Fig. 6, we demonstrate the inequality index, given by (24), for the UAV profits versus the maximum energy demand per ID. We notice that the SM provides higher fairness compared with RM and ECM, as each UAV is assigned to a CS based on mutually acceptable preferences. Recall that in Fig. 5, it is shown that the mean profit of the UAV operators is almost the same for SM and ECM. Hence, the capability of the SM to provide fairness among the UAV operators profits, specially in a lower IDs energy demand regime, is corroborated.

Finally, in Fig. 7, we illustrate the UAV utilization, i.e., a metric given by the ratio of the actual provided UAV

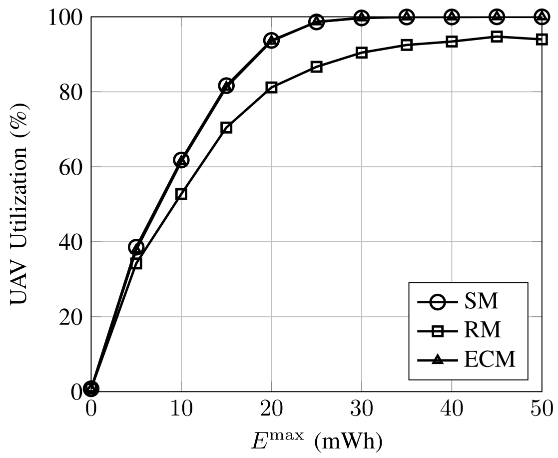

FIGURE 7. UAV utilization for the presented association techniques vs maximum energy demand per ID.

energy for ID charging to the total available UAV energy for ID charging. As expected, increasing $E^{\max}$ results in higher utilization. In fact, the point where the utilization saturates at 100% represents the optimal number of UAVs for this specific $E^{\max}$, since at this point all UAVs provide their available energy. More specifically, in the specific scenario with $C = 5$ and $U = 12$, if $E^{\max}$ is below 30 mWh, there is no need for more than 12 UAVs, since it would result in lower profit and fairness for some UAV operators, while providing the same total energy coverage. Therefore, through Fig. 7, it is possible to find the most profitable UAV number for a given $E^{\max}$.

VI. CONCLUSION

In this paper, we proposed a thorough framework that provides energy coverage to IDs by employing: i) UAV swarms with WPT capabilities, and ii) CSs that fulfil the UAV energy needs. By considering the incentives of the involved operators, we proposed a many-to-one matching game that assigns the UAVs into cells around the CSs. Owing to the inter-dependencies among the operators' utilities, a matching game with externalities was applied, while the existence of a two-sided stable matching was proved. Then, we designed a optimization scheme that conducts a UAV-CS assignment with the aim to maximize the energy coverage of the IDs. Finally, we verified through extensive simulations that the proposed matching algorithm achieves a near-optimal energy coverage performance, while exhibiting higher fairness among the operators' profits compared to the other schemes. As future directions of this work, data collection can be jointly investigated with WPT utilizing appropriate protocols, such as *harvest-then-transmit*, while the proposed framework can be extended by incorporating UAV trajectory design.

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