A UAV-enabled Dynamic Multi-Target Tracking and Sensing Framework

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***Abstract*—In this paper an Unmanned Aerial Vehicles (UAVs) - enabled dynamic multi-target tracking and data collection framework is presented. Initially, a holistic reputation model is introduced to evaluate the targets' potential in offloading useful data to the UAVs. Based on this model, and taking into account UAVs and targets tracking and sensing characteristics, a dynamic intelligent matching between the UAVs and the targets is performed. In such a setting, the incentivization of the targets to perform the data offloading is based on an effort-based pricing that the UAVs offer to the targets. The emerging optimization problem towards determining each target's optimal amount of offloaded data and the corresponding effort-based price that the UAV offers to the target, is treated as a Stackelberg game between each target and the associated UAV. The properties of existence, uniqueness and convergence to the Stackelberg Equilibrium are proven. Detailed numerical results are presented highlighting the key operational features and the performance benefits of the proposed framework.**

***Index Terms*—Unmanned Aerial Vehicles, Matching Theory, Reputation Model, Game Theory.**

I. Introduction

Unmanned Aerial Vehicles (UAVs) have attracted the interest of the research community due to their salient attributes, such as strong line-of-sight connection links, fast and flexible deployment and mobility. Their vital features have enabled them to support various civil Internet of Things (IoT) applications, such as surveillance systems [1]. UAVs have also been used for data collection from critical areas in crowdsourcing applications [2]. Motivated by these applications, in this paper we propose a UAV-enabled multi-target tracking and sensing framework, where the UAVs are matched to the targets based on a reputation model, and the optimal data collection is determined in a distributed manner by a game-theoretic approach.

A. Related Work & Motivation

Computer vision-based target tracking is proposed in the literature using the sparse representation theory to model the target's appearance [3]. In [4], the target tracking problem is formulated based on the partially observable Markov decision process framework, where input is provided by an on board camera. The joint problem of target tracking and UAV path planning is studied in [5], by using vision sensors, a laser scanner, and an on board embedded computer. A deep reinforcement learning (DRL) approach is proposed in [6] to deal with the target tracking problem, under the challenge of frequent changes of the target's aspect ratio. In [7], the authors determine the minimum number of UAVs that are needed to detect a set of targets by formulating a network flow-based problem and solving it with heuristic algorithms.

UAVs have also been used to support crowdsourcing IoT applications enabling the data collection from targets residing in critical areas, e.g., public safety scenarios. In [8], a UAV-assisted crowd surveillance use case is studied, where the UAVs collect videos from cameras on the ground and they process them either on board or at the ground servers. In [9], the UAV's flight time is minimized by optimizing its altitude, while jointly maximizing the number of offloaded bits by the ground devices. In [10], the joint optimization problem of the UAV's trajectory and radio resource allocation is studied via a successive convex approximation framework, to maximize the number of served devices in terms of achievable uplink data rate.

However, despite the significant advances achieved by these efforts, they either neglect or partially consider, the problem of stable matching among the UAVs and the targets, as well as the incentivization of the targets to provide their data to the UAVs. In this paper, we aim to address this research gap by introducing (i) a holistic reputation model to evaluate the targets' potential to provide useful data, (ii) an intelligent matching framework between the UAVs and the targets, and (iii) a game-theoretic approach to determine the targets' optimal amount of offloaded data to the UAVs, while following a pricing-based approach to incentivize them to perform the data offloading.

B. Contributions & Outline

The key technical contributions of this research work are summarized as follows.

- A reputation model is introduced to quantify the targets' reputation in terms of valuable offloaded data to the UAVs. It consists of (i) the *UAV-agnostic reputation*, where the targets' reputation is determined by all the UAVs, and (ii) the *trustworthy reputation*,

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where the evaluation of a trusted set of UAVs regarding the targets' reputation weighs more (Section II).

- Representative preference matching functions are formulated for the UAVs and the targets to capture their preferences in terms of pairing among each other. An intelligent matching algorithm is realized to decide the targets to be tracked by the UAVs (Section III).
- The targets and the UAVs utility from offloading and collecting data, respectively, is captured in utility functions. A Stackelberg game is formulated among each target and the associated UAV to determine each target's optimal amount of offloaded data and the effort-based price that the UAV offers to the target to incentivize it to offload its data. The properties of existence, uniqueness and convergence to the Stackelberg Equilibrium are proven (Section IV).
- A set of detailed numerical results is presented to evaluate the performance of the proposed framework, while a comparative study demonstrates its superiority in terms of successful target tracking and data collection (Section V).

II. Models & Assumptions

A. System Model

We consider a snapshot of a smart city environment consisting of a set of targets $I = \{1, \dots, i, \dots, |I|\}$ (e.g., ambulances, firetrucks, mobile IoT sensors), and a set of UAVs $N = \{1, \dots, n, \dots, |N|\}$. The position of each UAV at the time t is $p_t^n = (x_t^n, y_t^n, z_t^n)$. The target's position $q_t^i = (x_t^i, y_t^i, 0m)$ at time t is stochastic following a bivariate Gaussian distribution. Thus, the UAVs know the likelihood $\phi^i(q_t^i) : Q \to \mathbb{R}_{>0}$ that the target i is at a location q_t^i at time t. We obtain the highest likely probabilistic position $\hat{q}_t^i = (\hat{x}_t^i, \hat{y}_t^i, 0m)$ by employing the mean of the target's Gaussian distribution. Each UAV n is characterized by its normalized flying time $F_n \in [0, 1]$, which depends on its energy availability, where a value closer to one indicates a greater flying time. Each target i has a personal normalized cost $c_i \in (0, 1]$ (e.g., consumed energy) to collect the data $d_{i,n}$ that will be offloaded to a UAV n, thus, it charges the UAV with an effort-based price $P_{i,n}$ in order to obtain its data. For generalization purposes, we consider that the targets' data collection personal cost c_i and the effort-based price $P_{i,n}$ are unitless. Each target has a criticality factor $i_i \in (0, 1]$ based on the events in the surrounding environment. For example, an ambulance close to an area that a shooting occurred has greater criticality of data compared to a police car patrolling a neighborhood. The targets collect $D = \{1, \dots, d, \dots, |D|\}$ different types of data, e.g., videos, alerts, where $d \in (0, 1]$. A greater value of d represents an enhanced type of data, e.g., video, compared to a smaller value of d, which indicates a lower type of data, e.g., speed alert. The popularity of each type of data is captured by the Zipf distribution $Zipf(d) = \frac{z_1}{d^{z_2}}$, $z_1 > 0, 0 < z_2 < 1$.

B. UAV-agnostic Reputation Model

The UAVs track the targets and collect data from them in order to report them to a central entity, e.g., the Emergency Control Center (ECC) in a smart city. Each target is characterized by a reputation based on how helpful or not was the provided information. In the *UAV-agnostic reputation model*, all the UAVs evaluate the targets' reputation that they interact with, each one with equal weight. Towards the UAV n evaluating how helpful is the information collected by the target i, the following metric is introduced: $H_{i,n} = \frac{d_{i,n}}{P_{i,n}} \cdot Zipf(d)$. Its physical notion is that a UAV considers the provided data from target i helpful if the data collection process is cost-efficient (i.e., $\frac{d_{i,n}}{P_{i,n}}$) and the type of the collected data is of high popularity (i.e., $Zipf(d)$). Thus, a binary parameter represents if the collected data are helpful ($c_{i,n}^{\lambda} = 1$, if $H_{i,n} \geq H_{thr}$) or not ($c_{i,n}^{\lambda} = 0$, if $H_{i,n} < H_{thr}$) for the UAV n in the λ-th interaction with the target i, where $H_{thr} = \sum_{\forall i \forall n} H_{i,n}/|I|$.

The reputation of a target i, as it is evaluated by a UAV n, decreases as the most recent interaction time among them elapses, given that the UAV has not a recent evaluation regarding the target's data. A reputation decay function $\log_2(\frac{b}{T - t_{i,n}^{\lambda}} + 1)$ is introduced, where $t_{i,n}^{\lambda}$ is the time instance of the λ-th interaction among the UAV n and the target i, T is the time duration that we study the sytem, and $b > 0$ is the decay factor. After each UAV is associated with a target (Section III), the UAV n provides a good $GR_{i,n} = \sum_{\lambda=1}^{\lambda_{i,n}} c_{i,n}^{\lambda} \cdot \log_2(\frac{b}{T - t_{i,n}^{\lambda}} + 1)$ or a bad reputation $BR_{i,n} = \sum_{\lambda=1}^{\lambda_{i,n}} (1 - c_{i,n}^{\lambda}) \cdot \log_2(\frac{b}{T - t_{i,n}^{\lambda}} + 1)$ for the target i that is associated with, where $\lambda_{i,n}$ is the number of interactions among the target i and the UAV n in the examined duration T. Thus, the overall UAV-agnostic reputation that target i receives from UAV n, considering both its good and bad reputation, is derived as $UAR_{i,n} = \mathbb{E}(beta(GR_{i,n}+1, BR_{i,n}+1)) = \frac{GR_{i,n}+1}{GR_{i,n}+BR_{i,n}+2}$.

C. Trustworthy Reputation Model

In contrast to the UAV-agnostic reputation, there may be UAVs that their evaluation weighs more, e.g., UAVs belonging to the ECC, in the reputation score of a target. Thus, we determine the most trusted UAV $\hat{n} = \arg\min_{n' \in N} [\sum_{\substack{n \in N \\ n' \neq n}} |UAR_{i,n'} - UAR_{i,n}|]$ as the one that has the smallest difference from all the other UAVs for a specific target i. A UAV belongs to the set of trusted UAVs $N_{tr.,i}$ for a target i, if $|UAR_{i,\hat{n}} - UAR_{i,n}| \leq Tr_{thr}$, where $Tr_{thr} > 0$ is a trust threshold defined by the central entity.

The overall reputation of a target i combines the UAV-agnostic reputation and the trustworthy reputation. Thus, the overall good (Eq. 1) and the overall bad reputation (Eq. 2) of the target i is determined as follows.

$$OGR_{i,n} = w_1 \cdot GR_{i,n} + w_2 \cdot \sum_{n'=1}^{|N_{tr.,i}|} GR_{i,n'} \quad (1)$$

$$OBR_{i,n} = w_1 \cdot BR_{i,n} + w_2 \cdot \sum_{n'=1}^{|N_{tr.,i}|} BR_{i,n'} \quad (2)$$

where $w_1, w_2 \geq 0$ are the weighting factors of the UAV-agnostic and trustworthy reputation.

Thus, the overall reputation of the target i based on the evaluation of the UAV n is determined below.

$$R_{i,n} = \mathbb{E}(beta(OGR_{i,n}+1, OBR_{i,n}+1)) = \frac{OGR_{i,n}+1}{OGR_{i,n}+OBR_{i,n}+2} \quad (3)$$

III. Intelligent Multi-Target Tracking

In this section, an intelligent matching mechanism is introduced to pair each UAV with a corresponding target, while considering their tracking and sensing characteristics. Each UAV n has a preference function $M^t_{n,i}$ that captures its priority to track a target i in time t.

$$M^t_{n,i} = \frac{1}{|\hat{q}^i_t - p^n_t|} \cdot \frac{i_i}{P_{i,n}} \cdot \frac{R_{i,n}}{\sum\limits_{i \in I} R_{i,n}} \quad (4)$$

The physical notion of Eq. 4 is that a UAV prefers to track a target that is in its close proximity, has high criticality of collected data, provides its data in a competitive effort-based price, and it has a good reputation.

Each target i has a preference function $TM_{i,n}$ that captures its priority to offload data to a UAV n at time t.

$$TM^t_{i,n} = \frac{1}{|\hat{q}^i_t - p^n_t|} \cdot \frac{F_n}{c_i} \cdot \frac{R_{i,n}}{|UAR_{i,\hat{n}} - UAR_{i,n}|} \quad (5)$$

The physical notion of Eq. 5 is that a target i prefers to offload its data to a UAV n that (i) is in its close proximity, thus the target will spend less energy to offload the data; (ii) has a long flying time, thus the target has sufficient time to transmit its data; (iii) the target's data collection cost for the requested amount of data by the UAV n is low; and (iv) is trustworthy and has provided an overall high reputation for the target i.

Based on the above, we build the UAVs' and the targets' matching tables at time t, as $M^t = (M^t_{i,n})_{|I|\times|I|}$ and $TM^t = (TM^t_{i,n})_{|N|\times|N|}$, respectively. We consider $|N| = |I|$, and we are searching for a stable matching among the UAVs and the targets by examining the problem from the UAVs' perspective. Following the matching theory, we adopt the Gale-Shapley algorithm [11] to enable the UAVs to select the targets that will track at every examined time t. The main steps of the proposed multi-target multi-UAV matching algorithm are as follows.

1. At each time t, the UAVs and the targets have ranked the members of the opposite set based on their own preference function, i.e., Eq. 4 and Eq. 5, respectively.
2. Each UAV, which is not already paired with a target, will be randomly chosen to propose to its most preferable target (as indicated by the UAV's matching table M^t), which has not already rejected this UAV.
3. The target being proposed will: (i) accept the UAV's proposal, if this is the target's first received proposal; (ii) reject if this proposal is worse (in terms of the target's preference order of UAVs) than its current proposal; and (iii) accept if this proposal is better than its current one.
4. If all the UAVs are paired, the matching algorithm stops, otherwise returns to step 2.

The outcome of the multi-target multi-UAV matching algorithm is the stable pairs (i^*, n^*) of targets and UAVs.

IV. Optimal Sensing

In this section, the problem of optimal sensing, i.e., data collection from the smart city's field, is addressed. Given the pairs of UAVs and targets, the target's i utility by offloading $d_{i,n}$ data to the UAV n, is given as follows.

$$U_{i,n}(P_{i,n}, d_{i,n}) = P_{i,n} \cdot d_{i,n} - c_i \cdot d_{i,n} \quad (6)$$

where $c_i = \frac{k_i}{Zipf(d)}, k_i > 0$ is a personalized cost (e.g., energy cost) of the target i to collect the data of type d. The target's utility represents the revenue $(P_{i,n} \cdot d_{i,n})$ that the target gains by offloading its data, while considering its corresponding cost $(c_i \cdot d_{i,n})$ to collect the data.

The experienced utility of a UAV n by tracking a target i and collecting data from it, is formulated as follows.

$$\mathcal{U}_{n,i}(P_{i,n}, d_{i,n}) = \mu_n \cdot \log_2(1 + \sum_{i \in I} R_{i,n} d_{i,n}) - \sum_{i \in I} P_{i,n} d_{i,n} \quad (7)$$

where $\mu_n > 0$ is the UAV's n operation factor, i.e., level of contribution to the smart city's proper operation. It is noted that the UAVs belong to a central entity of the smart city, that controls the data collection operation. The first term of Eq. 7 represents the perceived utility of the UAV n by the available information in the smart city field that is collected by the targets. The second term of Eq. 7 represents the smart city central entity's total cost (charged by the targets) to collect the data.

Each target aims at maximizing its utility during the data collection process by determining the optimal effort-based price $P^*_{i,n}$ that will charge the UAV in order to provide its data $d_{i,n}$. Each target's utility maximization problem is formulated as follows.

$$\max_{P_{i,n}} U_{i,n}(P_{i,n}, d_{i,n}) \quad (8)$$

Similarly, each UAV aims at maximizing its own utility during the data sensing operation. Each UAV determines the optimal amount of data $d^*_{i,n}$ that it can receive from the target that is paired with, while providing the corresponding effort-based price. Each UAV's utility maximization problem is formulated as follows.

$$\max_{d_{i,n}} \mathcal{U}_{n,i}(P_{i,n}, d_{i,n}) \quad (9)$$

The two utility maximization problems of the target (Eq. 8) and the UAV (Eq. 9) are coupled together through the variables $P_{i,n}$ and $d_{i,n}$. Thus, we follow a two-step *Stackelberg game-theoretic approach*, where the target i is the leader and the UAV n is the follower. The Stackelberg game is played between a UAV n and a target i, thus, $|I|$ Stackelberg games are played in parallel at time t.

Towards determining the Stackelberg Equilibrium (SE) of each game, we perform a backward induction.

The UAV determines its optimal sensing demand of data $d^*_{i,n}$ requested from the target towards maximizing its utility, as follows: $\frac{\partial \mathcal{U}_{n,i}}{\partial d_{i,n}} = \frac{\mu_n R_{i,n}}{1+\sum\limits_{i \in I} R_{i,n} d_{i,n}} - P_{i,n}$ and $\frac{\partial^2 \mathcal{U}_{n,i}}{\partial d^2_{i,n}} = -\frac{\mu_n R^2_{i,n}}{(1+\sum\limits_{i \in I} R_{i,n} d_{i,n})^2} < 0$. We observe that $\mathcal{U}_{n,i}$ is strictly concave with respect to the requested amount of data $d_{i,n}$. Thus, it has a unique optimal amount of data $d^*_{i,n}$ determined as follows.

$$d^*_{i,n} = [\frac{\mu_n}{P_{i,n}} - \frac{1 + \sum\limits_{i' \in I, i' \neq i} R_{i',n} d_{i',n}}{R_{i,n}}]^+ \tag{10}$$

where $[x]^+, x \geq 0$. Based on Eq. 10, we derive the following observations: (i) the sensing demand of data $d_{i,n}$ of the UAV n is proportional to the target's i overall reputation and inversely proportional to the target's i effort-based price that charges the UAV; (ii) the targets compete with each other to gain a higher reputation by reducing the effort-based price, thus, reducing their personal cost.

The target's utility function (Eq. 6) can be rewritten as $U_{i,n}(P_{i,n}, d^*_{i,n}) = (P_{i,n} - c_i) \cdot [\frac{\mu_n}{P_{i,n}} - \frac{1+\sum\limits_{i' \in I, i' \neq i} R_{i',n} d_{i',n}}{R_{i,n}}]$, based on Eq. 10. It is noted that if the effort-based price $P_{i,n}$ that a target i charges a UAV n is high, this will impact the UAV's tracking decision (Section III), and the UAV may select another target to track. Thus, the target's optimal effort-based price $P^*_{i,n}$ is the Best Response to the other targets announced prices, i.e., $P^*_{i,n} = BR(\mathbf{P_{-i,n}})$, where $\mathbf{P_{-i,n}} = (P_{1,n}, \dots, P_{i-1,n}, \dots, P_{i+1,n}, \dots, P_{|I|,n})$. Towards proving the existence and uniqueness of an SE, we show that the target's utility function is strictly concave with respect to the effort-based price $P_{i,n}$, as follows: $\frac{\partial U_{n,i}}{\partial d_{i,n}} = \frac{\mu_n c_i}{P^2_{i,n}} - \frac{1+\sum\limits_{i' \in I, i' \neq i} R_{i',n} d_{i',n}}{R_{i,n}}$ and $\frac{\partial^2 U_{n,i}}{\partial d^2_{i,n}} = -\frac{2\mu_n c_i}{(P_{i,n})^3} < 0$. Thus, the best response strategy of the target i is:

$$P^*_{i,n} = BR(\mathbf{P_{-i,n}}) = \sqrt{\frac{R_{i,n} \mu_n c_i}{1 + \sum\limits_{i' \in I, i' \neq i} R_{i',n} d_{i',n}}} \tag{11}$$

Based on Eq. 10, 11, the SE is $(P^*_{i,n}, d^*_{i,n})$ for the Stackelberg game played among the UAV n and the target i. In order to prove the convergence of the target's i best response strategy to the SE, it suffices to prove that $P^*_{i,n} = BR(\mathbf{P_{-i,n}})$ is a standard function [12].

Theorem 1: Each target's $i, i \in I$, best response strategy $BR(\mathbf{P_{-i,n}})$ is a standard function.

Proof: Towards proving Theorem 1, the properties of positivity, monotonicity, and scalability should hold true.
1. *Positivity:* Based on Eq. 11, we have $BR(\mathbf{P_{-i,n}}) > 0$.
2. *Monotonicity:* Base on Eq. 10, 11, we have $BR(\mathbf{P_{-i,n}}) = \sqrt{\frac{R_{i,n} \mu_n c_i}{1+\sum\limits_{i' \in I, i' \neq i} R_{i',n} [\frac{\mu_n}{P_{i',n}} - \frac{1+\sum\limits_{i'' \in I, i'' \neq i} R_{i'',n} d_{i'',n}}{R_{i',n}}]}}$.

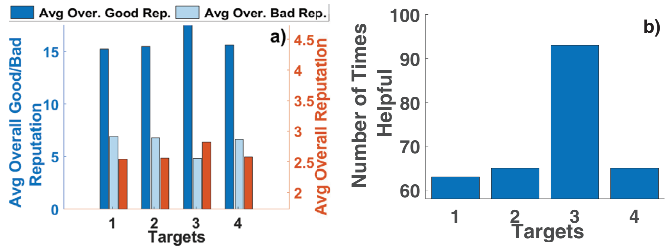

Fig. 1: Targets reputation model – Targets perspective

Thus, we observe that $P_{i',n}$ is proportional to $BR(\mathbf{P_{-i,n}})$. Therefore, the property of monotonicity is satisfied.
3. *Scalability:* The following property should hold true: $a \cdot BR(\mathbf{P_{-i,n}}) > BR(a \cdot \mathbf{P_{-i,n}}), a > 1$. We have: $\frac{a \cdot BR(\mathbf{P_{-i,n}})}{BR(a \cdot \mathbf{P_{-i,n}})} = \sqrt{\frac{a^2 + \sum\limits_{i' \in I, i' \neq i} a R_{i',n} [\frac{\mu_n}{P_{i',n}} - \frac{1+\sum\limits_{i'' \in I, i'' \neq i} R_{i'',n} d_{i'',n}}{R_{i',n}}]}{\sum\limits_{i' \in I, i' \neq i} R_{i',n} [\frac{\mu_n}{P_{i',n}} - \frac{1+\sum\limits_{i'' \in I, i'' \neq i} R_{i'',n} d_{i'',n}}{R_{i',n}}]}}$. Given that $a > 1$, we have $\frac{a \cdot BR(\mathbf{P_{-i,n}})}{BR(a \cdot \mathbf{P_{-i,n}})} > 1 \iff a \cdot BR(\mathbf{P_{-i,n}}) > BR(a \cdot \mathbf{P_{-i,n}})$. Thus, we conclude that $P^*_{i,n} = BR(\mathbf{P_{-i,n}})$ is a standard function with respect to $\mathbf{P_{-i,n}}$. ■

V. Numerical Results

In this section, a detailed numerical evaluation is presented in terms of (i) the proposed reputation model's success to capture the system's conditions (Section V-A); (ii) the performance of the intelligent matching algorithm (Section V-B); (iii) the operation of the game-theoretic sensing framework (Section V-C); and (iv) the benefits of the overall framework compared to other alternatives (Section V-D). For the purposes of the evaluation, the values of the considered key parameters are as follows: $|N| = |I| = 4, b = 0.5, Tr_{thr} = 0.1, w_1 = 0.6, w_2 = 0.4, z_1 = d^*_{i,n}, z_2 = 1/P^*_{i,n}$, an area of $100m \times 100m, z^n_t = 121m, T = 100, \mu_n = [1.115, 1.355, 1.675, 1.789]$, while F_n, i_i randomly distributed in $(0, 1]$. The proposed framework's evaluation was conducted in a HP Laptop, 1.8GHz Intel Core i7, with 16GB LPDDR3 available RAM.

A. Operation of Targets Reputation Model

In the following we examine the operation of the reputation model, both from the targets and the UAVs perspective. In particular, initially Fig. 1a presents the targets' average overall good (Eq. 1), overall bad (Eq. 2), and overall (combined) reputation (Eq. 3), over the time period of $T = 100$ time instances, while Fig. 1b depicts the number of times that the targets were providing helpful data to their associated UAVs. The results confirm that the targets with the highest average overall good reputation and the smallest average overall bad reputation conclude to better average overall reputation (Fig. 1a). Accordingly, as shown in Fig. 1b their provided data to the UAVs are evaluated as helpful more times.

Towards examining the operation of the proposed reputation model from the UAVs' perspective, Fig. 2a-2d

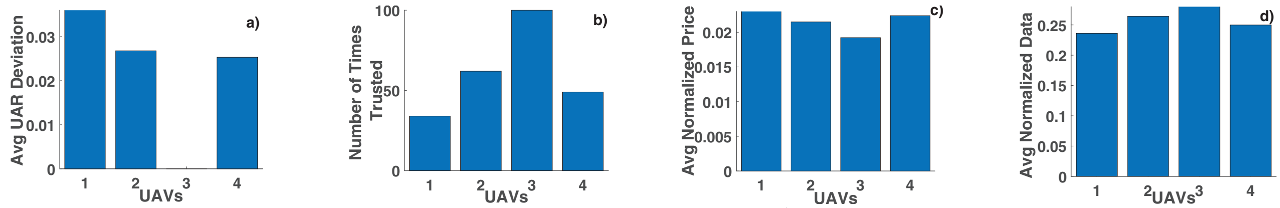

Fig. 2: Targets reputation model – UAVs perspective

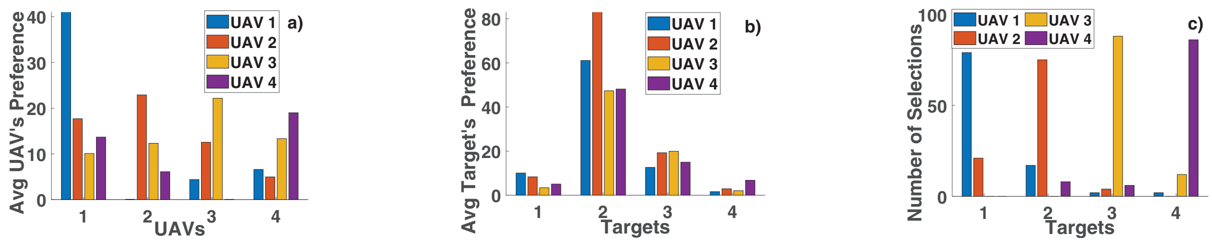

Fig. 3: UAVs – Targets intelligent matching

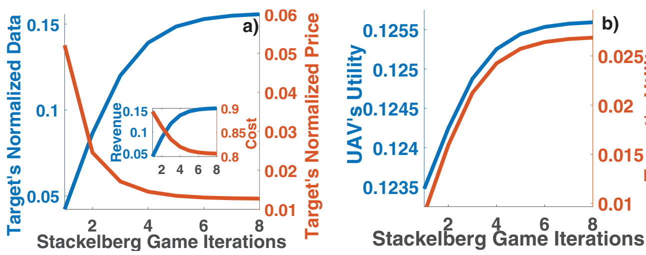

Fig. 4: Optimal sensing – Convergence to the SE

present the UAVs' agnostic reputation deviation from the most trusted UAV, i.e., $|UAR_{i,\hat{n}} - UAR_{i,n}|$, the number of times that each UAV belongs to the set of trusted UAVs $N_{tr.,i}$ of its associated target, the average normalized effort-based price that it experiences and the average normalized amount of data that it collects, respectively. We observe that the UAVs with the smallest deviation (Fig. 2a) are trusted more times (Fig. 2b). Thus, based on the outcome of the SE of each game among each UAV and its associated target, they collect more data (Fig. 2d) by investing a smaller effort-based price (Fig. 2c), thus collectively concluding to more cost-efficient data sensing.

B. UAVs – Targets Intelligent Matching Framework

The following results in Fig. 3a-3c demonstrate the operation and effectiveness of the introduced UAVs-targets matching framework, in terms of the UAVs' preferences (Eq. 4), the targets' preferences (Eq. 5), and the actual number of targets' selections by the UAVs for a time duration $T = 100$ time instances, respectively. Specifically, based on the results illustrated in Fig. 3a, it is observed that UAV 1 prefers to track target 1, UAV 2 prefers to track target 2, etc. The exact symmetric observation holds true regarding the targets' preferences to offload their data to the corresponding UAVs (Fig. 3b). It is noted that the proposed matching framework captures in a holistic manner both the UAVs and the targets matching preferences through the proposed preference functions, i.e., Eq. 4, 5, thus concluding to an overall successful matching outcome (Fig. 3c).

C. Optimal Sensing Framework Operation Evaluation

In the following, the operation of the optimal sensing framework (Section IV) is evaluated, and the convergence of the corresponding game to the unique SE is shown. The Stackelberg game between one UAV and the target that is associated with, is examined for one time instance t. Fig. 4a present the target's normalized offloaded data $d_{i,n}$ and the corresponding effort-based price $P_{i,n}$, as a function of the game's iterations. The enclosed subfigure presents the respective target's revenue and cost. Fig. 4b presents the target's utility $U_{i,n}$, and the UAV's utility $\mathcal{U}_{n,i}$ as a function of the number of iterations. The results reveal that the target's offloaded amount of data and the corresponding price (Fig. 4a) converge monotonically to the SE in few iterations (less than 8 iterations equivalent to 7msec). Following the outcome of the Stackelberg game, the target's and the UAV's utility (Fig. 4b) also monotonically converge to the optimal outcome given the uniqueness of the SE. Also, during the Stackleberg game's iterations, the target increases its revenue and decreases its cost by strategically deciding its offloaded data, while considering the effort-based pricing limitations (Fig. 4a).

D. Comparative Evaluation

In this section, initially we compare the proposed intelligent matching framework with the following three alternative matching approaches. (1) Ratio Approach: The UAVs select the targets that have high criticality of collected data and provide their data in a competitive effort-based price, i.e., $M^t_{n,i} = \frac{i_i}{P_{i,n}}$. The targets select the UAVs that have long flying time and its personal cost to collect the data is low, i.e., $TM^t_{i,n} = \frac{F_n}{c_i}$. (2) Reputation Approach: The UAVs and the targets define their preferences based on the reputation model, i.e., $M^t_{n,i} \frac{R_{i,n}}{\sum\limits_{i \in I} R_{i,n}}$, $TM^t_{i,n} = \frac{R_{i,n}}{|UAR_{i,\hat{n}} - UAR_{i,n}|}$. (3) Min Distance Approach: The UAVs' and the targets' preferences are defined based on the minimum distance between them, i.e., $M^t_{n,i} = TM^t_{i,n} = \frac{1}{|\hat{q}^i_t - p^n_t|}$.

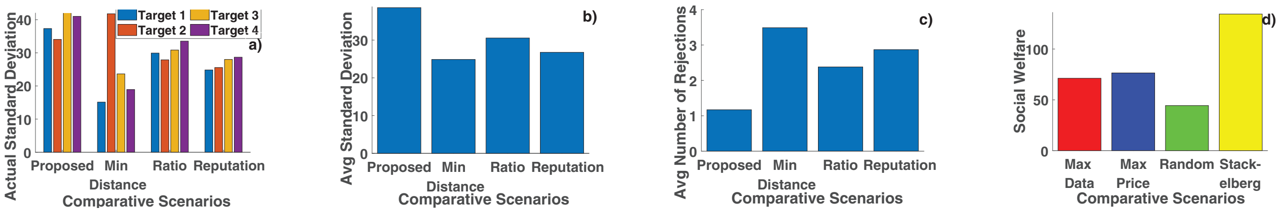

Fig. 5: Comparative Evaluation

Fig. 5a and Fig. 5b present the actual standard deviation of the number of selections of each UAV from the most selected target and the corresponding average standard deviation over all the targets in the system for all the comparative approaches, respectively. Furthermore, Fig. 5c presents the corresponding average number of rejections, i.e., two UAVs preferred the same target and due to conflict one UAV's preference was rejected. The results reveal that under the proposed matching framework, the UAVs experience few conflicts among each other (Fig. 5c), while they tend to select their most preferable target, and therefore the actual (Fig. 5a) and average (Fig. 5b) standard deviation of the number of selections from their most preferable selection is high. The Ratio approach presents also small number of conflicts among the UAVs (Fig. 5c) compared to the Reputation and the Min Distance approaches, due to the great variation of the UAVs' preference function given the personalized price $P_{i,n}$ that target i charges UAV n. In the Reputation approach, all the UAVs tend to select the most reputable targets, while in the Min Distance approach, the closest targets. Thus, in those two approaches, the number of rejections is high (Fig. 5c) and the actual (Fig. 5a) and average (Fig. 5b) standard deviation of the number of selections from their most preferable selection are consequently low.

Additionally, we compare the proposed optimal sensing framework against the following three alternatives: (1) Max Data Scenario: All targets offload their total amount of collected data. (2) Max Price Scenario: The targets charge the UAVs with a fixed (maximum) price. (3) Random Scenario: The targets decide randomly the amount of data to offload and the price to charge. For fairness purposes, in all comparative approaches, the intelligent matching algorithm introduced in this paper, is adopted. The social welfare of the system, i.e., the summation of the targets' (Eq. 6) and the UAVs' utilities (Eq. 7), is presented in Fig. 5d for all the considered comparative scenarios for $T = 100$ time instances. The results clearly reveal the superiority of the proposed optimal sensing framework, while the Max Data and the Max Price scenarios both present similar low social welfare levels, and the Random approach provides the worst outcome.

VI. Conclusions

In this paper, a novel holistic UAV-enabled multi-target tracking and sensing framework is introduced. Initially, each target's reputation is defined, consisting of both UAV-agnostic and trustworthy reputation models. Based on that, the intelligent pairing of the UAVs with the targets towards enabling the multi-target tracking by the UAVs, is performed. The targets' optimal data offloading strategies along with the optimal effort-based price that the UAVs are charged with in order to collect the targets' data, are determined based on a Stackelberg game-theoretic approach. Detailed numerical results were presented highlighting the key operational features and the performance benefits of our proposed approach. Part of our current and future work focuses on treating the examined problem based on a labor economics approach under the principles of Contract Theory, towards incentivizing the targets to offload their data to the UAVs.

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