Security Service Pricing Model for UAV Swarms: A Stackelberg Game Approach

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***Abstract*—Unmanned Aerial Vehicles, popularly known as UAVs, have been used in many applications, from healthcare services to military assignments with diverse capabilities such as data transmission, cellular service provisioning, and computational offloading tasks. UAV's have been recently used to provide Security as a Service (SaaS). SaaS involves technical solutions like anti-virus and anti-spam software, firewalls, using secure operating systems, etc. UAV's are resource-constrained devices, and thus they are connected to the base station (BS) so that they may avail the computational facilities of the BS. The UAV's connect themselves to the base station using cluster heads (intermediary devices). At times several UAVs cooperatively come together to serve a given region and such a group of UAVs is called a swarm of UAVs. In real-world scenarios, many stakeholders come together to form UAV swarm configuration proving services to users. Each stakeholder wants to maximize his gains. In this work, we propose a pricing Stackelberg game among UAVs, Cluster heads, and BS by formulating their behavioral utilities. Using particle swarm optimization on each entity's utility functions, we create an optimal price strategy for each entity to maximize their profit.**

***Index Terms*—UAVs, Security, Service provider, Stackelberg, Game Theory.**

I. INTRODUCTION

Unmanned aerial vehicles (UAVs) have become a significant research domain due to their real-world applications like service provisioning, edge computing, security, surveillance, etc. UAV swarms can provide services to a large number of users in a wide geographic area. Most end-user get services from UAV based on a subscription model. UAV stakeholders gain the profit based on revenue generated from end-users and costs of availing services from the base station. SECaaS includes authentication, anti-virus, anti-malware/spyware, intrusion detection, penetration testing, security event management, etc. SECaaS eases the end-user's financial constraints and provides opportunities for end-user integrated security solutions without the requirement of high-end hardware devices. SECaaS also provides continuous protection to distributed users and provides the most recent security coverage.

With higher competition among the stakeholders to take the customer shares and optimize their resources, the UAV swarms are generally formed by heterogeneous entities belonging to different associates. Each of these stakeholders wants to maximize its profit. In such scenarios, the naive greedy-based approach is not stable and may result in imbalance among stakeholders. So there is a need for optimal strategy among the stakeholders, where each participating entity's gain is mutually maximized.

Various literature approaches such as [1, 2, 3, 4] have been designed to solve the optimization problem for the multi-stakeholder system. However, there is still no work that addresses the optimal pricing strategy for stakeholders in the UAV-BS model. Most previous works have taken an underline assumption that all UAVs belong to the same stakeholder. This paper addresses pricing in UAV swarms by proposing a game-theoretic formulation of the UAV SECaaS scenario.

The organization of the paper is as follows. Section II discusses the related works. Section III presents the system model, and Stackelberg game formulation is described in section IV. The following section (Section V) optimizes entities' utility functions and evaluates the solution using particle swarm optimization. Section VI discusses the simulation and results. The conclusion of the paper is presented in Section VII.

II. RELATED WORKS

SECaaS as a whole is becoming one of the most important "software as a service" [5]. UAVs are becoming an alternative to traditional edge or cloud services as they are more accessible to users. Moreover, they can cater to moving users and can avoid obstructions in communication with the user [6]. Many researchers have been working with the application of UAVs [7, 8, 9, 10, 11] to find solutions for efficient provisioning of services like anti-virus and anti-spam software, firewalls, using secure operating systems, etc. Shakeri et al., [12] investigated the BS-UAV domain and discusses

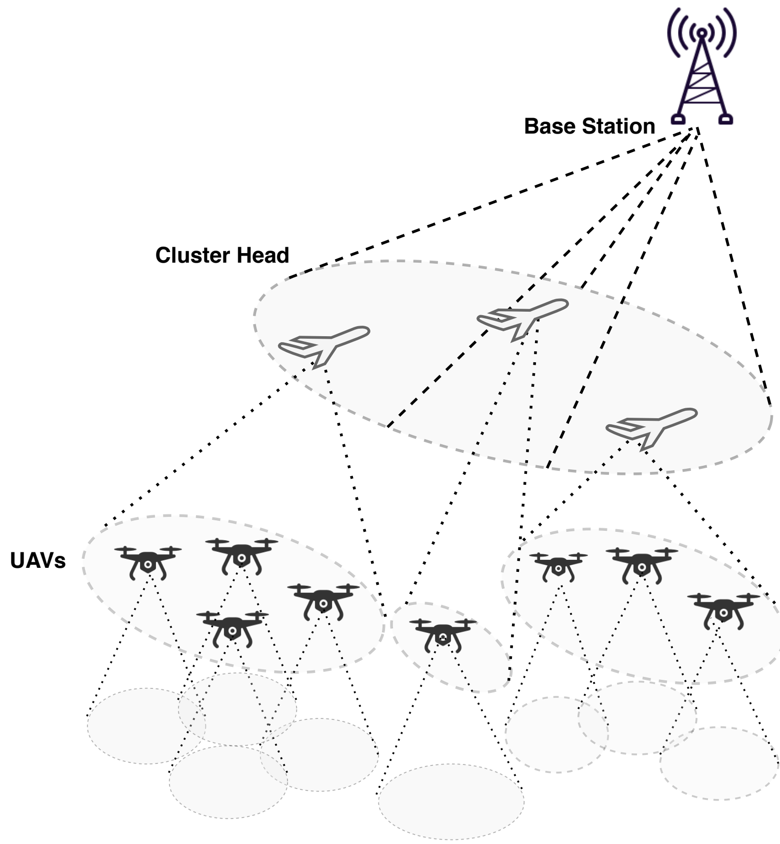


Fig. 1: Two stage buyer seller model

the pricing strategy model as one of the research challenges for future research. Alladi et. al, [13] also discusses the challenges in BS UAV domain.

As discussed by [12], the major challenge is the optimal pricing model for maximizing UAV network applications' gains. BS are connected to UAV through hop fashion, where cluster head acts as an intermediary. Resources come at a cost, and therefore there is a need to maximize the gains for the participating stakeholders. There is also a need for proper utility formulations for base stations, cluster heads, and UAVs [4, 14]. A deep reinforcement learning model was designed by [15], which tried to create a system-based utility function. They employed reinforcement learning to find the optimal solution. Their reward function used the sigmoid function on task offloading and energy consumption. However, their model had drawbacks. Firstly, these techniques take a much longer time to converge. Secondly, the optimization was performed on the whole system, where entities are considered selfless, which does not hold real-world applications. Other proposed models include static and dynamic schemes. Static schemes like [16] involve prices being set at the beginning of the iteration of allocation, thus making the complexity of the problem too simple (not practical in the real-world scenario). This model is unrealistic as the base station and provides agreed levels of services without any incentive. Many dynamic schemes such as [**?**] were proposed to resolve the issue with static schemes, which involved the allocation of service demand based on auctioning priority optimization.

This paper proposes a Stackelberg game formulation and uses particle swarm optimization to achieve the best solution. We mathematically optimize the utility function for different price values and show optimum pricing strategy and resource allocation.

III. System Model

Security as a service (SECaaS) is used to leverage security services to end-user based on the subscription model. The subscription model uses service demand or the number of self-defense goods as the measure of service. 'Self-defense' goods imply a cluster head's efforts to secure their system through technical solutions such as anti-virus anti-spam software, firewalls, using secure operating systems, etc. This paper presents a hierarchical network architecture between the UAV, cluster heads (CHs), and base stations. UAVs are connected to CH, and CHs are connected to BS. UAVs pay the CH based on CH's service demand, and CH pays to BS for service demand provided by BS. The demand for UAV is given by r_{ji}. The pricing policy and behavioral utility model consider the amount of service received by the entity and the cost it has to pay. This model considers one base station providing sufficient service demand denoted by R^{MAX}.

We consider there is an M number of clusters, each headed by cluster heads. Each cluster can have a variable number of serving UAV denoted by N_i, where i is the cluster number. The iterator for UAV is denoted by j. Any UAV can be uniquely identified in the system using (i, j) (Cluster it belongs to and UAV number in the cluster). The service requirement by UAV or service demand offered by i^{th} CH to j^{th} UAV is given r_{ji}. Each entity has a utility function based on its behavior. CH acts as buyer to BS and seller to UAV. p_i is the price demanded by CH from UAVs in its clusters, and P denotes the price charged by BS from CH based on aggregate service it demands. This paper proposes a two-stage buyer-seller Stackelberg game model that proposes an optimal solution for entities using particle swarm optimization.

IV. Game-Theoretic Formulation

This section will formulate a two-stage Stackelberg game (between BS and CH and between CH and UAV). The utility of an entity is defined in terms of the net profit that the entity earns. An entity's profitability is the difference between the revenues earned from its customers and the costs associated with the buyer's purchase of services.

A. Utility of UAV

In the system model, multiple UAV are connected to a single CH, and such multiple CH connect to a BS. For j^{th} UAV in the i^{th} cluster we denote the offered service demand to UAV as r_{ji}. The utility of device is based logarithmic function of demand as used in [17] and [18]. The value of utility increases by log of demand and decreases by price paid p_i to i^{th} CH for each unit of service. So the utility of UAV is given by $U_{\text{UAV}_{ji}}$:

$$U_{\text{UAV}_{ji}} = K(\ln(r_{ji})) - p_i * r_{ji}. \tag{1}$$

Here, K is the proportionality constant or price that UAV receives from the user for a particular gain $((\ln(r_{ji})))$. K has units similar to p_i.

As different stakeholders have different gain benchmark [19] of profit, and thus, each UAV has a limit on the minimum utility to function $U^{min}{}_{\text{UAV}_{ji}}$. Different stakeholders have different expectations of return. For, e.g., industry giants like Google, Amazon is likely to invest in a considerable revenue return compared to startup or small-scale firms. So there is a difference in utility thresholds of different UAVs. Using the utility threshold and above stated equation for utility, we can formulate the bound on the price. This bound on price is called the price threshold or the maximum price that UAV can pay. Any increase of price beyond this limit would eventually decrease the utility of UAV beyond the threshold, and thus entity would be unwilling to participate.

Each UAV tries to choose an optimal value of r_{ji} according to CH's rate. This can be formulated as:

B. Utility of Cluster Head

CH generates its profit by selling the service to UAV in its cluster and pays the price to BS for claiming the resources to satisfy the requirements. Let the number of UAV that is part of i^{th} CH at the instant be n_i. P denotes the price that BS charges from CH for each unit of service. In this scenario, we consider that the cluster head offers the same price to all the UAVs in its cluster. So the utility of CH for i^{th} cluster can be formulated as:

$$U_{\text{CH}_i} = \sum_{j=1}^{n_i} p_i r_{ji} - P \sum_{j=1}^{n_i} r_{ji}, \tag{2}$$

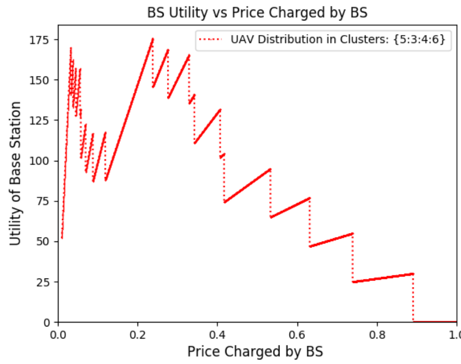
C. Utility of Base Station

The base station increases the price P, which it charges from the cluster head to maximize the profit. However, the utility function is not a linear function with P. Increasing the price would increase the utility. But as we have discussed already, if the price is increased beyond a limit, UAVs do not participate in-game.

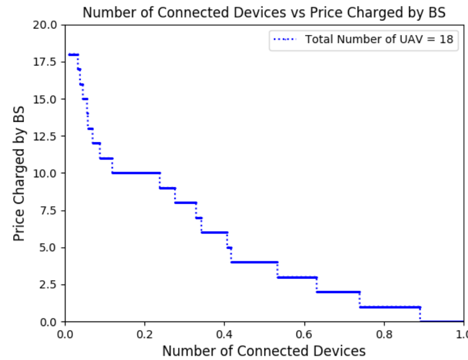
$$\begin{aligned} \max_{P} \quad & U_{\text{BS}} \\ \text{s.t.} \quad & \sum_{i=1}^{M} R_i \leq R_{\text{MAX}}. \end{aligned} \tag{3}$$

V. Utility Optimisation

In this section, we try to optimize all the entities' utility by formulating the Stackelberg game. The



(a) Utility of BS vs P



(b) Number of Connected Users vs P

Fig. 2: Variation of Utility of BS & Number of Connected UAV vs P

Stackelberg game uses the leader-follower model. The leader chooses a move, and then the followers follow. In this model, the base station is the leader, and UAVs or CHs are followers. As the base station is a resource provider, it has an incumbent monopoly of the market. So it decides to choose its strategy. Based on the values of price chosen by BS, CH chooses the price, and UAVs set their demands. In the Stackelberg game, the leader moves first, and the followers follow sequentially. The constraint is once the leader has made its move, it cannot undo it - it is committed to that action. UAVs or CHs can't predict BS pricing action. The outcome of strategic interaction is evaluated using Nash equilibrium [20]. Nash equilibrium is the current strategy policy that an entity makes based on a previous course of actions in the game. It can be proven that no entity can increase its utility by choosing other strategy-keeping strategies of all other entities fixed.

It can be observed from the model that price P sets a constraint on the pricing of cluster heads and thus on UAVs. Since the function increases with P, the base station's utility increases for P's small values, but when P is increased beyond a certain threshold, the UAVs start disconnecting. As we already discussed, no entity participated in-game if its utility decreases beyond a threshold. So, as P is increased beyond a threshold, the revenue of BS starts decreasing. Since the relationship between P and p_i is not linear, the relationship between the utility and P is not linear. Thus there exists many local maxima and minima (can see figures in the result section). To find the optimal pricing of cluster head (p_i) based on P can be evaluated using any heuristic-based optimization technique like particle swarm optimization (PSO) [21] proposed in 1995. PSO algorithm uses iterative optimization technique, trying to improve the solution concerning function. BS chooses a price and solves the maximum pricing strategy for cluster heads p_i using PSO. These price values can be mathematically proved to have a maximum value of CH and UAV optimization function. And there does not exist any other better value of p_i that increases the system's utility.

VI. Simulation and Results

This section simulates our model using python on Macbook Air, 1.8 GHz Dual-Core Intel Core i5 with 8GB RAM. Table **??** presents value used in simulation. We consider a scenario consisting of 4 Cluster heads CH1, CH2, CH3, and CH4 and the numbers of UAV in respective clusters be 5, 3, 4, and 6. The threshold utility or the maximum utility of UAV depends on the value of K and is randomly chosen for simulation.

Using the threshold or maximum utility, we evaluate the maximum price or threshold price for UAV (presented in table I).

TABLE I: Price Threshold

K	**Price Threshold**
10	{0.16, 0.29, 0.35, 0.53, 0.58, 0.83}
20	{0.11, 0.15, 0.30, 0.38, 0.74, 0.86}
30	{0.104, 0.18, 0.40, 0.53, 0.73, 0.89}
40	{0.14, 0.24, 0.35, 0.44, 0.54, 0.76}

Fig. 2 depicts the utility of the base station with changing the price charged by BS from CH. K set as 30 for all the UAVs. P is varied from 0.01 to 1. Fig. 2 (a) shows that as P increases, the utility of BS increases due to higher gains from cluster heads. But gradually, when P is increased beyond a certain threshold, the number of connected UAVs starts disconnecting. An increase in P causes an increase in p_i for UAV for cluster heads to maintain their utility. As UAVs disconnect, there is a loss of revenue for both CH and BS. Thus, the plot between the utility of BS and P shows a jagged pattern. Fig. 2 (b) shows the disconnection of UAVs with an increase in P, where the sudden change happens for optimal p_i evaluated using PSO.

VII. Conclusion

This paper presents a two-stage buyer-seller model for security as a service. The UAV swarm model consists of multiple UAVs buying security services in exchange for price from the base station via cluster heads. Cluster heads act as middle man or intermediaries between the transactions of UAVs and BS. Each entity is heterogeneous and considered selfish. All participating devices try to maximize their gain by maximizing their utility functions. The buyer-seller model is formulated in terms of the Stackelberg game, where the optimal pricing and resource allocation are calculated based on particle swarm optimization.

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