UAV SECaaS: Game-Theoretic Formulation for Security as a Service in UAV Swarms

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***Abstract*—Unmanned Aerial Vehicles, popularly known as UAVs, have been used in many applications in the recent past. UAV's have also been recently used to provide Security as a Service (SECaaS). SECaaS involves technical solutions like anti-virus and anti-spam software, firewalls, using secure operating systems, etc. UAV's are resource-constrained entities, and thus, they avail the computational facilities of the Base Station (BS) to serve the users in their range. At times, several UAVs cooperatively come together to serve a given region, and such a group of UAVs is called a swarm of UAVs. Generally, a group/swarm of UAVs connect themselves to the base station through cluster head UAVs, which are intermediary nodes. In real-world scenarios, many stakeholders come together to form a UAV swarm configuration providing services to users. Each stakeholder wants to maximize gains. This work proposes a pricing Stackelberg game among the UAVs, cluster heads, and the BS by formulating their behavioral utilities. Using particle swarm optimization on each entity's utility functions, we create an optimal price strategy to maximize profit.**

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

I. Introduction

With a wide spectrum of users in a given geographic area, generally, the security requirements for each user vary. Some users may require more security services from the service provider, while others may opt for the baseline default security. For example, a user running financial services is likely to need more security measures than a user providing basic web hosting. Security provisioning using UAVs is an emerging area of exploration for service providers where service providers use UAVs to provide resources to their customers to secure their data or perform verification tasks. Security services often include authentication, anti-virus, anti-malware/spyware, intrusion detection, penetration testing, security event management, etc [1, 2]. The core infrastructure for providing security in these models is built at the base station, and the UAV provides wide user access and reachability.

Security provisioning can be categorized into different service models such as Software as a Service (SaaS), Platform as a Service (PaaS), and Infrastructure as a Service (IaaS). Recently, there has been a paradigm shift from IaaS to SaaS, with companies like Amazon, Google, and Microsoft putting efforts to provide security as a SaaS for users. Security as a service is commonly referred to as SECaaS [3]. SECaaS offers security services to end-users based on the subscription model, which can enable cost reduction, improve the quality of existing operations and provide rapid service [4, 5].

UAVs, being computationally limited, are not themselves the end resource providers. Instead, they act as intermediary resource providers, where the service resources are hosted at the base station. UAVs act as the buyer to the base station and seller to users [6]. At times, several UAVs cooperatively come together to serve a given region, and such a group of UAVs is called a swarm of UAVs. Generally, these swarm of UAVs connect themselves to the base station through cluster head UAVs, which act as intermediary nodes. These intermediary nodes save most of the energy consumption of UAVs that goes wasted in long-range communication with base station [7, 8]. They also improve the performance of terrestrial wireless communications. These cluster heads also allow a more significant number of dedicated UAVs and assist in planning trajectories to cover a wider geographic area. Additionally, these intermediary UAVs can assist transmission of base communication devices by ferrying resources between the base station and UAVs [9, 10].

There is a fundamental challenge in managing the UAV-based Security as a service solution to identify who manages the resources and UAV networks [11, 12]. Generally, these networks of UAVs, cluster heads, and base stations belong to different stakeholders. Different companies come together to participate in service provisioning and gain profit [13–15]. Different service providers like Microsoft, Google, Amazon, etc., form the core resource provider (base station). The stakeholders of participating entities (UAVs, cluster heads, and base stations) try to find an optimal strategy to maximize their gains. UAVs try to maximize the profit by selling to end-users and buy at a lower price from cluster heads. Similarly, the cluster head maximizes the profit from the difference in the amount it charges from UAVs, and it has to pay to the base station. This paper addresses these issues by formulating a buyer-seller model for Security as a Service between the base station, the cluster heads, and the UAVs (as shown in Fig. 1).

The major contributions of this manuscript are highlighted as follows:

1) We formulate a buyer-seller model between the base station, the cluster heads, and the UAVs for SECaaS

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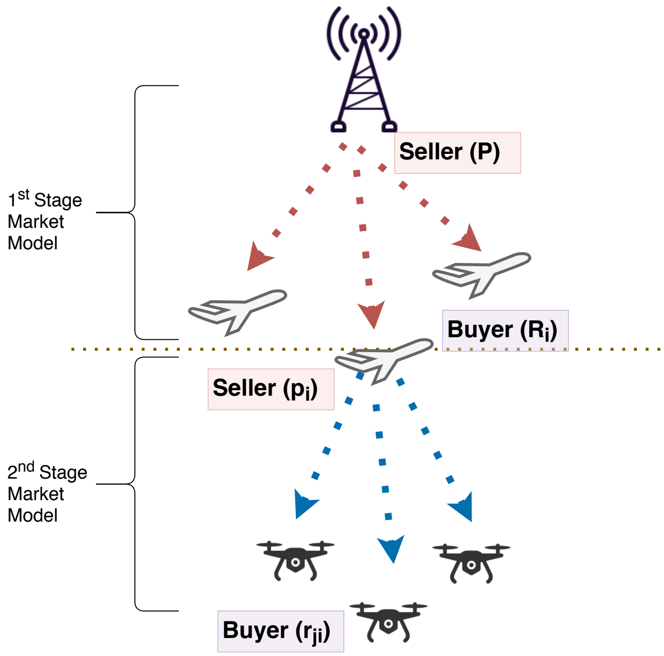


Fig. 1: Two stage buyer seller model

provisioning using UAVs.
2) We propose a Stackelberg game to find an optimal solution for price and demand distribution that maximizes the profit of all the participating entities
3) The paper does not make any assumptions on the behavior of entities in terms of utility and accommodates different entities' different profit thresholds.
4) We also show the impact of pricing strategy/profit gains as a function of various network parameters.
5) This paper presents the first work on the pricing-based game-theoretic application for hierarchical UAV networks.

The organization of the paper is as follows. Section II discusses the related works existing in the literature. Section III presents the system model, and the Stackelberg game formulation is described in Section IV. 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

UAVs are becoming an alternative to traditional edge or cloud services as they are more accessible to users and can accommodate moving users [16]. Security as a Service as a whole is emerging as one of the most important element of "software as a service" paradigm [17]. Many works such as [18–22] have been proposed to find viable and optimal solutions for efficient provisioning of services like anti-virus and anti-spam software, firewalls, using secure operating systems, etc.

In 2019, Shakeri et al., [23] investigated the open challenges for future research for BS-UAV domain. One of the major challenge involved development of an optimal pricing model for UAV-Base station applications. Many UAV-BS applications involve exchanges of resources like energy, data, money etc. The authors argue that all the resources come at a cost, and therefore, there is a need to maximize the gains for the participating stakeholders. This has been highlighted in [24] also. In [25], the authors assert the need of proper utility formulations for base stations and UAVs. The need of utility function based on pricing incentive was proposed in [26]. In here, authors considered three stakeholders, the UAVs, the cluster heads or the intermediaries and the base station.

Among the pricing models, a deep reinforcement learning model is designed in [27], that uses profit utility function for the entire network. The authors employed reinforcement learning to find the optimal solution for utility optimisation. However, their model has several 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 is not valid in real-world applications. Thirdly, the model does not take in account utility functions for each individual entities. Other proposed models include static and dynamic schemes. Static schemes like that proposed in [28] involve prices being set at the beginning of the iteration of allocation which is not practical in real-world scenarios. Many dynamic schemes such as [29, 30] were proposed to resolve the issue with static schemes, which involve the allocation of service based on auctioning priority optimization.

In [31], Yan et al. proposed a pricing mechanism that used a non-cooperative game formulation. The authors of [32] proposed an iterative pricing algorithm for peer to peer UAV-enabled wireless communication system. As the UAV relay nodes have no incentive to provide service, the pricing mechanism becomes a necessary method to encourage them to participate in communications to achieve more payments [31, 33]. The pricing mechanisms can maximize the revenue, enhance social welfare, and ensure user fairness [34]. Although there are many models, there is no concrete optimization formulation for pricing strategy in a hierarchical network of swarms.

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 is an attractive option 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' [35] implies 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 metric has been widely used in existing literature [36, 37] to quantify security resources. The other name used in [36, 37] for self-defense goods is Cyber

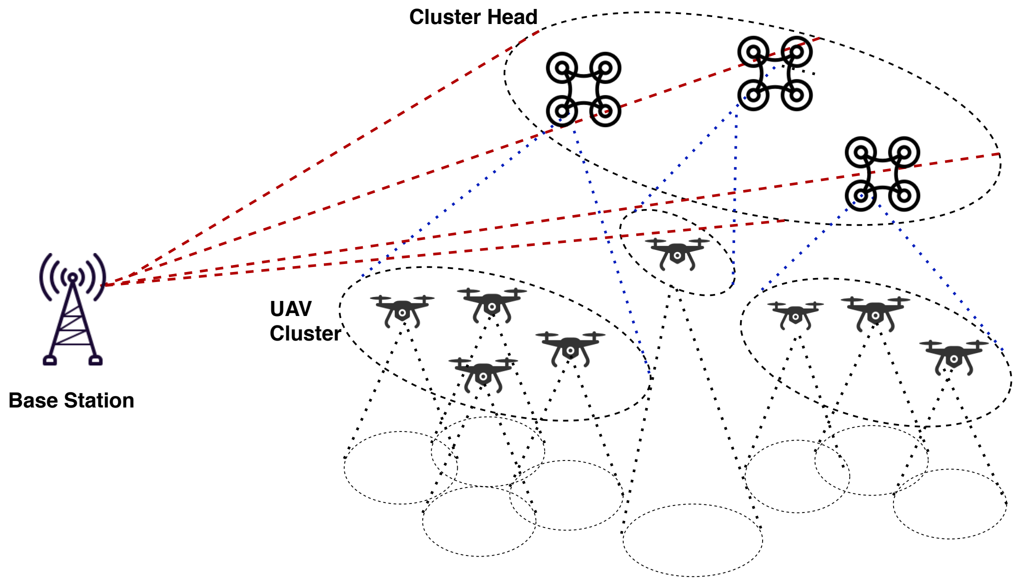


Fig. 2: System model.

Insurance. Cyber-insurance can be seen as a risk management technique via which network end-users transfer their risks to an insurance company (e.g., base station or cloud provider) in return for a fee, i.e., the insurance premium.

This paper presents a hierarchical network architecture between the UAVs, cluster heads (CHs), and base stations (Fig. 2). A group of UAVs providing service to a given region is referred to as a cluster, and each cluster is connected to a base station using a cluster head (CH). UAVs receive services from their cluster head depending on the amount that a UAV pays to its CH. Whereas CHs act as resource buyers for base stations.

The base station is connected to M clusters in our model, where a cluster head heads each cluster. Each cluster has a different number of UAVs denotes by N_i, where the subscript i refers to cluster number. Any UAV can be uniquely identified in the system using (i, j) (cluster it belongs to and UAV number in the cluster). The demand for service from a UAV is denoted 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. p_i is the price demanded by a CH from UAVs in its cluster, and P denotes the price charged by a BS from a CH based on the aggregate service it demands. This paper provides a two-stage buyer-seller Stackelberg game model that proposes an optimal solution for entities using particle swarm optimization.

IV. Notations

The notations used in this paper are described in Table I.

Notation	Defination
UAV_{ji}	j^{th} UAV in i^{th} cluster
p_i	Price charged by i^{th} CH per service unit
$\mathrm{U}_{\mathrm{UAV}_{ji}}$	Utility of j^{th} UAV in i^{th} cluster
K	Price that UAV receives from the user
r_{ji}	Service demand of the UAV_{ji}
$\mathrm{U}^{min}{}_{\mathrm{UAV}_{ji}}$	Minimum Utility Value for UAV_{ji}
$\mathrm{U}_{\mathrm{CH}_i}$	Utility of i^{th} cluster head
U_{BS}	Utility of base station
P	Price charged by BS per service unit
R_i	Total resource requirement from the BS
n_i	Number of UAVs in i^{th} cluster
M	Number of Clusters
$\mathrm{R}_{\mathrm{MAX}}$	Max. resource available to the BS
$p_{j,i}^{\mathrm{MAX}}$	Price threshold for UAV_{ji}
$\mathrm{I}ter^{\mathrm{MAX}}$	Max. Number of Iterations
$\mathrm{G}_{p^{``}}^{max}$	Global Best Value at $p^{``}$ in PSO iteration
$\mathrm{K}_{p^{`}}^{max}$	Particle Best Value at $p^{`}$ in PSO iteration
v	Velocity of particle in PSO
w	Inertia weight constant in PSO
c1,c2	Exploratory constants in PSO

TABLE I: Notations

V. Game-Theoretic Formulation

In this section, we formulate the utility values of the participating entities, namely the BSs, CHs, and UAVs. Also, we 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 [38, 39].

A. *Utility of* UAV

Our system model consists of many UAV connected to a single CH and multiple CH connected to a BS. Recall that for the j^{th} UAV in the i^{th} cluster, we denote the service demand of the UAV as r_{ji}. Existing literature [40] shows that the utility of a device is well modeled as a logarithmic function of the demand. This utility function has been widely used in several scenarios, and its behavior has also been modeled in [41]. The value of the utility increases by a log of demand and decreases by the price paid p_i to i^{th} CH for each unit of service. Thus, the utility of UAV_{ji} is given by:

$$\mathrm{U}_{\mathrm{UAV}_{ji}} = \mathrm{K}(\ln(r_{ji})) - p_i \times r_{ji}. \tag{1}$$

where 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 discussed earlier, different stakeholders have different gain benchmarks of profit [42], and thus each UAV has a limit on the minimum utility to function $\mathrm{U}^{min}{}_{\mathrm{UAV}_{ji}}$. Different stakeholders have different expectations of return. For example, large organizations like Google and Amazon are more likely to invest in a significant revenue return than startups or small-scale firms. Thus, there is a difference in utility thresholds of different UAVs. Using the utility threshold and above-stated equation for utility, we can formulate abound on the price. This bound on price is called the price threshold or the maximum price that a UAV can pay. Any increase in price beyond this limit would eventually decrease the UAV's utility beyond the threshold, and thus, it would be unwilling to participate.

Each UAV tries to choose the optimal value of r_{ji} so as to maximize its utility. The utility function of the UAV can be given as:

$$\max_{r_{ji}} \ \mathrm{U}_{\mathrm{UAV}_{ji}}, \tag{2}$$
$$\text{s.t. } \mathrm{U}_{\mathrm{UAV}_{ji}} \geq \mathrm{U}^{min}{}_{\mathrm{UAV}_{ji}}.$$

B. Utility of Cluster Head

A cluster head generates its profit by selling the service to UAV*s* in its cluster and incurs a loss for purchasing the resources from the BS. Let the given instant be n_i. P denotes the price that the 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 the i^{th} cluster can be formulated as:

$$\mathrm{U}_{\mathrm{CH}_i} = \sum_{j=1}^{n_i} p_i r_{ji} - \mathrm{P} \sum_{j=1}^{n_i} r_{ji}. \tag{3}$$

Note that $\sum_{j=1}^{n_i} p_i r_{ji}$ denotes the total revenue earned by the cluster head and $\mathrm{P} \sum_{j=1}^{n_i} r_{ji}$ denotes the total expenses it had to pay. The CH can not choose the price the BS demands. Also, it cannot decrease the demand for resources to be lower than the UAV's aggregate demand in the cluster. So the utility of cluster head primarily becomes a function of p_i. A cluster head can find the optimal price that needs to be charged from UAVs to maximize utility. Increasing the price would increase the utility. However, as we have discussed before, UAVs do not participate in-game if the price is increased beyond a limit. The minimum utility of the threshold is 0. Any negative utility results in the loss of stakeholders, and such stakeholders would be unwilling to participate. The objective function of the cluster head is given as:

$$\max_{p_i} \ \mathrm{U}_{\mathrm{CH}_i}, \tag{4}$$
$$\mathrm{R}_i = \sum_{j=1}^{n_i} r_{ji}.$$

where R_i is the aggregate of the UAV's total resource requirement in the cluster.

C. Utility of base station

The base station is the resource center. All the infrastructure and resources for services are built at the base station. Aggregated stakeholders or a single entity stakeholder may build the base station. We restrict the complexity of this problem to a single stakeholder resource station (e.g., Amazon-based cloud). The base station earns a profit by the number of services that it sells. The price for each of the services is set at P per unit of service. All the cluster heads connected to a BS are charged the same price, P. Recall that R_i is the total resource requirement of i^{th} cluster head. Let the total number of cluster heads connected to the base station by M and n_i be the number of UAVs connected to the i^{th} cluster head. The total earning of the BS can then be formulated as:

$$\mathrm{U}_{\mathrm{BS}} = \sum_{i=1}^{\mathrm{M}} \mathrm{P}\mathrm{R}_i. \tag{5}$$

To maximize the profit, the base station increases the price P which it charges from the cluster heads. However, the utility function is not a linear function with P. Increasing the price would increase the BS's utility. However, as discussed earlier, if the price is increased beyond a limit, UAVs do not participate in-game. So the optimisation problem for base station is:

$$\max_{\mathrm{P}} \ \mathrm{U}_{\mathrm{BS}}. \tag{6}$$
$$\text{s.t. } \sum_{i=1}^{\mathrm{M}} \mathrm{R}_i \leq \mathrm{R}_{\mathrm{MAX}}.$$

VI. Utility Optimisation

In this section, we try to optimize all the utilities of entities by formulating a Stackelberg game. The Stackelberg game uses the leader-follower model [43]. The leader chooses a move, and then the followers follow. In the proposed 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 price values chosen by the BS, CHS chooses their price, and UAVs set their demands. In the Stackelberg game, the leader moves first, and the followers follow sequentially [44]. The constraint is that once the leader has made its move, it cannot undo it - it is committed to that action. UAVs or CHs cannot predict the BS's pricing action. The outcome of this strategic interaction is evaluated using the Nash equilibrium [45]. The Nash equilibrium is the current strategy policy that an entity makes based on the previous course of actions in the game. It can be proved that no entity can increase its utility by choosing another strategy while keeping the strategies of all other entities fixed.

A. Optimal Utility for UAVs

Since the utility of an UAV is convex function, we can can find the optimal requirement for the j^{th} UAV connected to the i^{th} CH, by evaluating the partial derivative of the utility function and equating to 0. We have: $\frac{\partial \mathrm{U}_{\mathrm{UAV}\, ji}}{\partial r_{ji}} = 0$:

$$\mathrm{U}_{\mathrm{UAV}\, ji} = \mathrm{K}(\ln(r_{ji})) - p_i * r_{ji}. \tag{7}$$

$$\frac{\partial \mathrm{U}_{\mathrm{UAV}\, ji}}{\partial r_{ji}} = \frac{\mathrm{K}}{r_{ji}} - p_i. \tag{8}$$

Equating $\frac{\partial \mathrm{U}_{\mathrm{UAV}\, ji}}{\partial r_{ji}} = 0$, we get he optimal service demand for the UAV as:

$$r^*_{ji} = \frac{\mathrm{K}}{p_i}. \tag{9}$$

Also, the optimal utility at the optimal service demand is:

$$\mathrm{U}_{\mathrm{UAV}}{}^*_{ji} = \mathrm{K}\left(\ln\frac{\mathrm{K}}{p_i} - 1\right). \tag{10}$$

From (10), since $\mathrm{U}_{\mathrm{UAV}}{}^*_{ji} \propto \frac{1}{p_i}$, as p_i increases, $\mathrm{U}_{\mathrm{UAV}}{}^*_{ji}$ decreases.

The maximum price per unit of service that on UAV can pay is p^{MAX}_{ji}. 'Beyond this price value $p^{\mathrm{MAX}}_{j,i}$, the utility of the UAV will fall below the minimum. Hence, the UAV will not be interested in being a part of the game anymore. This maximum price is given by:

$$p^{\mathrm{MAX}}_{j,i} = \mathrm{K}\exp\left\{-\left(\frac{\mathrm{U}^{min}{}_{\mathrm{UAV}_{ji}}}{\mathrm{K}} + 1\right)\right\}. \tag{11}$$

B. Optimal Price Evaluation for CH

Using the optimal service requirement of the UAVs, we can formulate the best response strategy of the i^{th} CH as:

$$\begin{aligned}\mathrm{U}_{\mathrm{CH}_i} &= \sum_{j=1}^{n_i} p_i r^*_{ji} - \mathrm{P}\sum_{j=1}^{n_i} r^*_{ji} \\ &= n_i\left(\mathrm{K} - \mathrm{P}\frac{\mathrm{K}}{p_i}\right).\end{aligned} \tag{12}$$

Here we replace r_{ji} with the UAV's optimal service demand r^*_{ji}. The value of $\mathrm{U}_{\mathrm{CH}_i}$ initially increases with increasing p_i for fixed value of P. However, when p_i is increased beyond the UAV's price threshold, the UAV will not participate in-game, as its utility reduces rapidly. Hence a UAV will only participate when $p_i \leq p^{\mathrm{MAX}}_{j,i}$. Also, n_i will change only when p_i is changed between threshold price values for different UAVs. Any change of prince between the threshold does not change the n_i but increases the utility monotonically. So the optimal value of price p^*_i for CH comes for one of the threshold values.

C. Optimal Price Evaluation for BS

The utility of the BS can be evaluated using the optimal price of the i^{th} CH (p^*_i) as:

$$\begin{aligned}\mathrm{U}_{\mathrm{BS}} &= \sum_{i=1}^{\mathrm{M}} \mathrm{P}\mathrm{R}_i \qquad (13)\\ &= \sum_{i=1}^{\mathrm{M}} \mathrm{P}\sum_{j=1}^{n_i} r^*_{ji} \qquad (14)\\ &= \sum_{i=1}^{\mathrm{M}} \mathrm{P} n_i \frac{\mathrm{K}}{p^*_i}.\end{aligned}$$

where R_i is the aggregation of the service demand of the individual UAVs ($\sum_{j=1}^{n_i} r^*_{ji}$).

It can be observed from the model that the price P sets a constraint on the pricing of cluster heads and thus on UAVs. The base station's utility increases for small P values, but when P is increased beyond a certain threshold, the UAVs start disconnecting. As discussed earlier, no entity participates in-game if its utility decreases beyond a threshold. So, as P is increased beyond a threshold, the revenue of the 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, many local maxima and minima (readers can refer to Fig. 6 (a)). To find the optimal pricing of cluster head (p_i) based on P, we use particle swarm optimization (PSO).

Eberhart and Kennedy first proposed particle swarm optimization (PSO) [46] in 1995. PSO algorithm uses an iterative optimization technique, trying to improve the function governing the solution. PSO is a metaheuristic algorithm that can quickly find the optimal value over an ample space and does not make any assumptions regarding the problem. The main advantage of PSO over other evolutionary techniques is that it is not based on gradient descent. As a result, a function that is not differentiable can also be optimized by PSO. Inspired by birds and fishes' swarms, the algorithm uses candidates placed randomly in the search space. Each candidate calculates the value of the function, which is also called the fitness level. The optimization problem aims to determine the optimum value where all candidates converge to give a unique solution.

The next iteration's candidate movement is guided by two factors, their current optimum value and global maximum values given by $\mathrm{K}^{max}_{p'}$ and $\mathrm{G}^{max}_{p^*}$ respectively (shown in Algorithm 1). Exploratory constants set the rate of change of movement v and the inertia weight constant. The best or the most optimal position in the entire space that is discovered becomes the guide of the swarm's movement for the next iteration. This process is repeated again and again over several iterations until all candidates converge.

Algorithm 1: Particle Swarm Optimisation Algorithm

Output: Point at which Optimum Function Value is achieved

Notation:

F ← Utility function of Base station

P ← Initialize the particles randomly and assign particles randomly to search space

p ← Iterator for P

$Iter^{\text{MAX}}$ ← Max. Number of Iterations

$G^{max}_{p^{“}}$ ← Global Best Value at $p^{“}$

$K^{max}_{p^{‘}}$ ← Particle Best Value at $p^{‘}$

old ← current iteration

new ← next iteration

v ← velocity

w ← Inertia Weight Constant

c1,c2 ← Exploratory constants

while $i \le Iter^{\text{MAX}}$ **do**

  for p^{old} *in P* **do**

    Check if p^{old} *is in boundary conditions else update* p^{old}

    if $F^{old}_{p} > G^{max}_{p^{“}}$ **then**

      $G^{max}_{p^{“}} = F^{old}_{p}$

      $K^{max}_{p^{‘}} = F^{old}_{p}$

      $p^{“} \leftarrow p^{old}$

      $p^{‘} \leftarrow p^{old}$

    else

      flag ← *1*

    if $F^{old}_{p} > K^{max}_{p^{‘}}$ & *flag == 1* **then**

      $K^{max}_{p^{‘}} = F^{old}_{p}$

      $p^{‘} \leftarrow p^{old}$

    else

      flag ← *2*

    $v^{new} = w * v^{old} + c1 * (K^{max}_{p^{‘}} - p^{old}) + c2 * (G^{max}_{p^{“}} - p^{old})$

    $p^{new} \leftarrow p^{old} + v^{new}$

    Check if p^{new} is in boundary conditions else Algorithm 2 update p^{new}

  $i \leftarrow i + 1$;

  $p^{old} \leftarrow p^{new}$

return p^{old}

However, it is not always guaranteed to find the optimal solution because of PSO parameters' choice. PSO may also converge at local maxima or minima. Therefore, selecting the suitable PSO parameters is the subject of research [47]. All the UAVs in the network have a minimum threshold on the utility, which they need to maintain. Entities set this threshold utility at the beginning of the game. A price threshold is evaluated based on the utility threshold, assuming that the demand for UAV's service requirement is constant. This price threshold denotes the maximum price that a UAV can offer to a CH, after which its utility will go beyond the threshold, and the UAV will likely not participate

Algorithm 2: Algorithm for checking Boundary Condition

Input : Takes an input p^{old}

Output: Outputs the value of p within bounds (B^{min}, B^{max})

(B^{min}, B^{max}) ← Bounds of Search Space

if $p^{old} < B^{min}$ **then**

  $p^{new} = p^{old} + (B^{min} - p^{old})$

  if $p^{new} > B^{max}$ **then**

    $p^{new} = B^{max}$

if $p^{old} > B^{max}$ **then**

  $p^{new} = p^{old} + (p^{old} - B^{max})$

  if $p^{new} < B^{min}$ **then**

    $p^{new} = B^{min}$

  return p^{new}

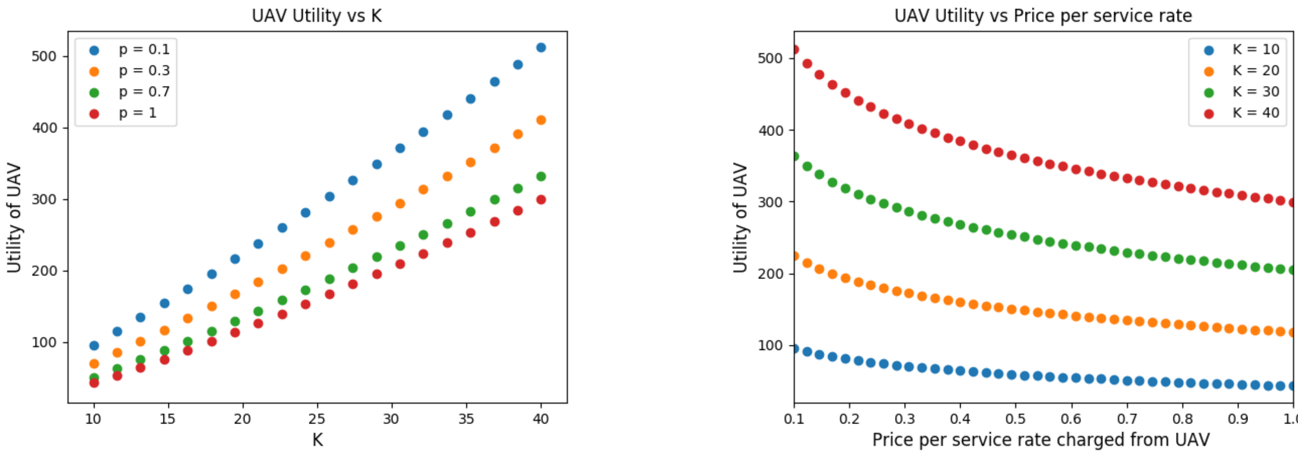
in the game. Using PSO, the BS chooses a price and solves the maximum pricing strategy for cluster heads, p_i. These price values can be mathematically proved to achieve the maximum value of CH and UAV optimization function. Note that there is no other better value of p_i that increases the system's utility. The overview of the algorithm is presented in Algorithm 1. To constrain particles to explore inside the desired solution space throughout the optimization process, we use our boundary conditions in particle swarm optimization (PSO) methods, as shown in Algorithm 2. We use limited boundary constraints in this paper to force errant particles to be moved inside the allowed solution space. It takes p^{old} as input and checks if it is between bounds B^{min}, B^{max}. If yes, p^{new} is returned as p^{old}. If $p^{old} < B^{min}$, $p^{new} = p^{old} + (B^{min} - p^{old})$, else if $p^{new} > B^{max}$, $p^{new} = B^{max}$. Similar check is done for other boundary conditions.

VII. Simulation and Results

In this section, we present our simulation results to evaluate the proposed system. The simulations have been conducted using python on 1.8 GHz Dual-Core Intel Core i5 with 8GB RAM. Table II gives the values of the variables used for the simulations and particle swarm optimization. We consider a scenario consisting of 4 cluster heads CH1, CH2, CH3, and CH4 and the numbers of UAVs in the respective clusters are 5, 3, 4, and 6. The threshold utility or the maximum utility of UAV depends on the value of K, and it is chosen randomly for simulations based on values presented in Table III.

K has units of price, and is varied for values in the set [10\$, 20\$, 30\$, 40\$] . The price charged by the cluster head p_i varies from 0.1 to 1 \$ per unit, while price charged by the base station varies from 0.01 \$ to 1\$. Using the threshold or maximum utility value, we evaluate maximum price or threshold price for an UAV (presented in Table IV) using:

$$p^{\text{MAX}}_{j,i} = \text{K} \exp\left\{-\left(\frac{\text{U}^{min}{}_{\text{UAV}_{ji}}}{\text{K}} + 1\right)\right\}.$$



(a) $\mathrm{U}_{\mathrm{UAV}_i}$ vs K.

(b) $\mathrm{U}_{\mathrm{UAV}_i}$ vs p_i.

Fig. 3: Variation of $\mathrm{U}_{\mathrm{UAV}}$

TABLE II: Values of Variable Used in Simulation

Variable	**Value**
Number of Clusters	4
No. of Users in each cluster	5,3,4,6
Range of K Values	10,20,30,40
Range of p_i Values	{0.1 - 1}
Range of Values for P	{0.01 - 1}
$\mathrm{R}^{\mathrm{MAX}}$	500
Number of PSO Particles	300
Number of PSO Iteration	30000
Particle Velocity Constant	0.1
Exploratory Constant	0.7
Acceleration Factor	1.5
Inertia Weight factor	0.01

TABLE III: Utility Threshold

K	**Utility Threshold**
10	{30.8, 25.1, 23.4, 19.2, 18.4, 14.8}
20	{83.1, 77.2, 63.5, 59.1, 45.8, 42.7}
30	{139.9, 122.8, 99, 90.9, 81.1, 75.5}
40	{185.4, 163.7, 149.2, 140.1, 131.5, 118.3}

TABLE IV: 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}

Figure 3 shows the variation in the utility of an UAV with K (Fig. 3 (a)) and p_i (Fig. 3 (b)). The price set by the BS is fixed at 0.05. In Fig. 3 (a), we vary the values of K in range between 10 to 40 for 4 different p_i values 0.1, 0.3, 0.7, 1. The utility threshold for all the UAVs is chosen from Table II. It can be observed from the figure that for a fixed p_i, the utility of UAV increases with K. This figure also depicts the impact of K in the utility as p_i is varied. On the other hand, Fig. 3(b) shows the decrease in UAV utility with an increase in the price that has to be paid by the UAV to the CH.

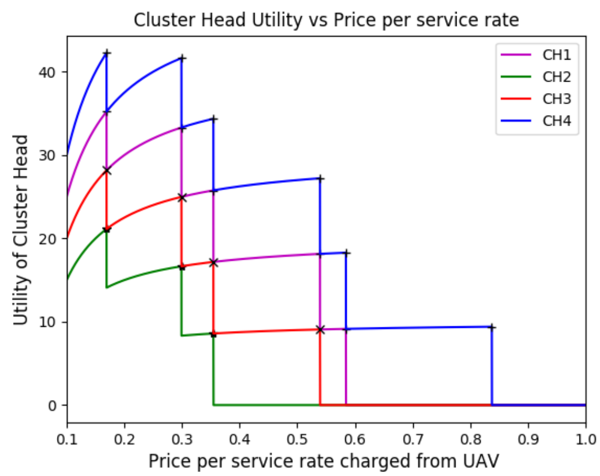
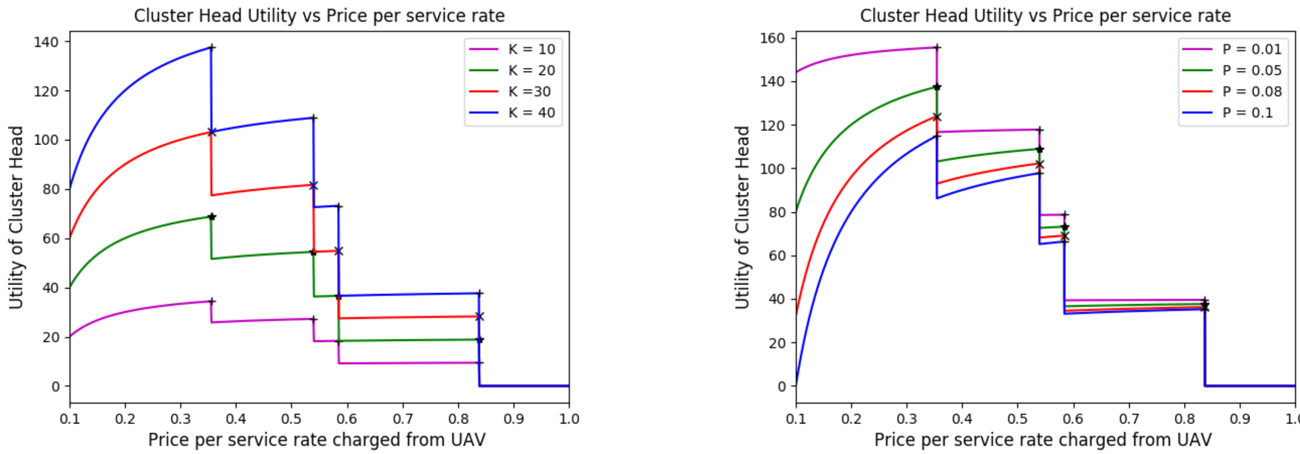


Fig. 4: Utility of CH_i vs p_i

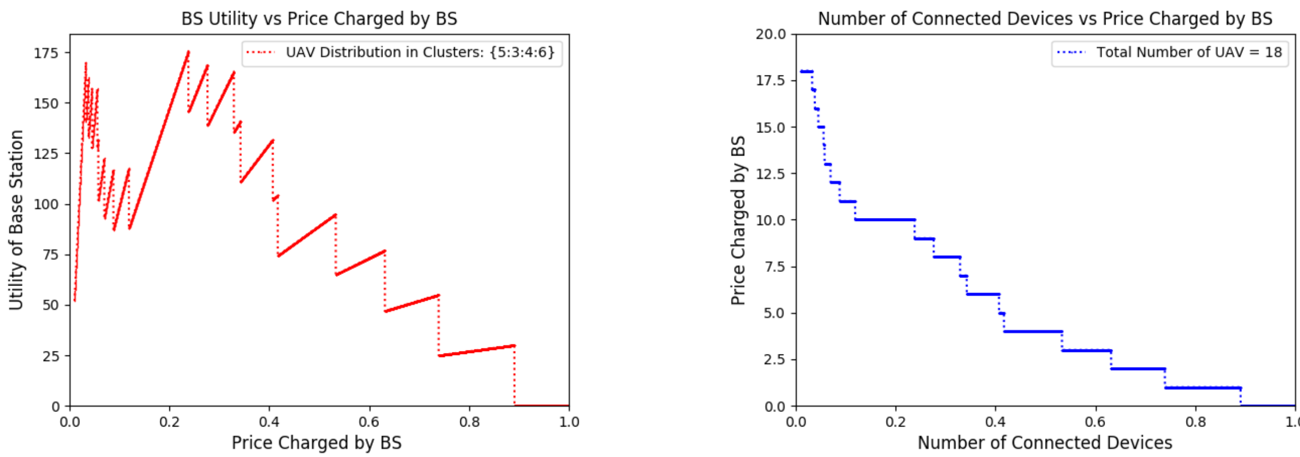
The utility decreases when p_i price charged is increased by different cluster heads (shown in Fig. 4). The price charged by the base station is fixed at 0.05$. All the UAV clusters are assumed to have the same K value set to 30. The only difference among clusters is the number of UAVs that are connected to a cluster. The first cluster head is connected to 5 UAVs, second to 3 UAVs, third to 4 UAVs, and fourth CH to 6 UAVs. The utility threshold and the price threshold values are chosen from Table I and Table II, respectively, for K = 30. From Fig. 4, we can see that the utility of a CH increases initially with an increase in p_i as more revenue is earned. However, as p_i increases beyond the threshold values of prices of a UAV, the utility drops abruptly. This is because, beyond the threshold value, the UAV will incur a loss. So the UAV gets disconnected and



(a) U_{CH_3} vs p_3 for different K.

(b) U_{CH_3} vs p_3 for different P.

Fig. 5: Variation of U_{CH_3}.



(a) U_{BS} vs P.

(b) Number of connected users vs P.

Fig. 6: Variation of U_{BS} and number of connected UAV vs P.

does not participate anymore.

The utility rises again with increasing p_i until a threshold value of another UAV is achieved. The rise in utility is due to higher revenue generated from remaining UAVs. After that, it will again drop due to UAVs disconnecting. Thus, the utility of BS as a function of P forms a zigzag pattern. Finally, the utility falls to 0 when P are increased beyond all devices' maximum threshold. The figure also shows that the cluster head's utility depends upon the number of UAVs connected to it. For example, the utility of cluster head 1 (CH1)(pink line) is higher in comparison to cluster head 2 (CH2)(green line) as CH1 is connected to 5 UAVs in comparison to 3 UAVs in CH2.

Figure 5 shows the variation in the cluster head utility as a function of the price p_i for different values of K and P for cluster 3. 4 UAVs are connected to cluster head 3. In Fig. 5 (a), we plot the utility of the CH vs. p_i where K takes values as [10, 20, 30, and 40]. P is fixed to 0.05. We observe that for a given p_i, the utility of cluster head increases with the increasing value of K. The peaks in the corresponding graph to the price thresholds, after which the utility drops abruptly. Figure 5 (b) shows the variation in the utility of cluster heads as a function of P for fixed K. K is varied from [0.1, 0.3, 0.7, 1]. The figure shows that with an increase in the value of P, the utility of cluster head decreases. The CH has to pay more to the base station for the same amount of service. Then, to maximize its utility, the CH has to increase its price resulting in gradual disconnection of UAVs.

Figure 6 depicts the utility of the base station as a function of the price charged by the BS from the CH. The UAV distribution is 5, 3, 4, and 6 for 4 clusters, with K set as 30 for all the UAVs. P is varied from 0.01 to 1. Figure 6 (a) shows that as P increases, the utility of BS increases due to higher gains from cluster heads. Gradually, when P is increased beyond a certain threshold, some of the connected UAVs start disconnecting. An increase in P causes an increase in p_i for UAVs in order for cluster heads to maintain their utility. As UAVs disconnect, there is a loss of demand and revenue for CH and BS. Thus, the plot between the utility of BS and P shows a jagged pattern. Figure 6 (b) shows the disconnection of UAVs with an increase in P. For every P, and we evaluate the optimal p_i using PSO.

VIII. Conclusion

This paper presents a two-stage buyer-seller model for security as a service provisioning in UAV swarms. The UAV swarms model consists of multiple UAVs buying security services from the base station via cluster heads. Cluster heads act as middlemen or intermediaries between the transactions of UAVs and the BS. Each entity is heterogeneous and regarded as selfish. All participating devices try to maximize their gain by maximizing their utility functions. The buyer-seller model is formulated in the Stackelberg game, where the optimal pricing and resource allocation are calculated based on particle swarm optimization. Further, in our simulation study, we show the impact of different parameters on the optimal allocation strategy.

IX. acknowledgment

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