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Optimized Unmanned Aerial Vehicles Deployment for Static and Mobile Targets Monitoring

Fadi Al-Turjman[1], Hadi Zahmatkesh[2], Ibrhaim Al-Oqily[3], and Reda Daboul[1]

[1]Department of Computer Engineering, Antalya Bilim University, Antalya, Turkey.

[2]Department of Computer Engineering, Middle East Technical University, Northern Cyprus Campus.

[3]The Hashemite University, P. O. Box 150459, Zarqa 13115, Jordan and Al-Yamamah University, P.O. Box 45180, Riyadh 11512, Saudi Arabia.

E-mails: fadi.alturjman@antalya.edu.tr, hadi.zahmatkesh@gmail.com, ialoqily@ieee.org, reda.dabol@antalya.edu.tr

***Abstract*—** In the recent decade, drones or Unmanned Aerial Vehicles (UAVs) are getting increasing attention by both industry and academia. Due to the support of advanced technologies, they might be soon an integral part of any smart-cities related project. In this paper, we propose a cost-effective framework related to the optimal placement of drones in order to monitor a set of static and/or dynamic targets in the IoT era. The main objective of this study is to minimize the total number of drones required to monitor an environment while providing the maximum coverage, which in turn leads to significant reduction in cost. Our simulation results show that by increasing the battery capacity of the drones, the drones' visibility range would also increase and thus, the number of drones would be reduced. Moreover, when the targets are sparsely distributed across a large number of different regions, a further increase to the targets does not require an increase in the number of drones needed to monitor them.

***Index Terms*—Smart city, Unmanned Aerial Vehicle (UAV), Drone, Internet of Things (IoT).**

1. Introduction

In recent decade, due to massive growth in the telecommunication sector, there is a high demand for providing high quality services. Moreover, the rapid growth in population and increase in the number of mobile connected devices have brought several challenges such as network coverage and capacity. One promising way to overcome such challenges is to utilize intelligent systems towards smart projects such as smart cities. Smart cities [1] are led by strategic administrations that support technology and innovation. The aim of smart cities is to maximize the efficient use of valuable resources to foster sustainable growth. Unmanned aerial vehicle (UAV) is considered a crucial part of smart cities. The main objective of a smart city is to improve its resident's life by providing low-cost services and efficient infrastructure. UAVs are already being used to document accident scenes [2], support first responder activities, and monitor construction sites [3], but they are ready to become an integral part of a smart city's network as well. UAVs can be used to gather key intelligence data on movements of potential threats and to help in determining locations of threats and providing detailed topographic information in real time. They can also be utilized in providing an accurate representation of an area using images, which can help to rescue human and animals in case of a disaster [4]. In addition, it is important to develop model-based controllers in order to monitor the movement of the UAVs in real-time. In this regard, discrete event modelling of embedded systems can be used as a formal method to develop software for embedded systems in order to implement the system software as a model [44].

The concept of smart city is converting cities into digital societies, transforming the life of its citizens to an easy life in every facet, and intelligent transport system (ITS) becomes an indispensable component among all. ITS [5] is considered as the application of sensing, control, analysis, and communication technologies to ground transportation in order to enhance security and mobility as well as efficiency. It includes a wide range of applications that process and share information to ease congestion, enhance traffic management, minimize environmental impact, and increase the benefits of transportation to commercial users and the public in general. As our contributions, we propose a cost-effective framework to minimize the total number of drones needed to monitor an area while providing the maximum visionary coverage for the target. In other words, we optimize the number and location of drones to have full coverage of an area which in turn reduces the overall cost of the network.

In order to fully understand drones and the proposed framework in this study, we first discuss various applications of drones in smart cities. The concept of smart city is based on the integration of Information and Communication Technology (ICT) and its trends. Smart cities play a significant role in development of a sustainable environment and drones play a major role in it as well. Drones are widely utilized in various areas. Their applications can be classified into environmental- and industrial-based applications. Some typical ones of these applications are listed and described in the following subsections.

1.1 Environmental-Based Applications

Drones or UAVs are becoming increasingly popular for monitoring the environment. The technology has entered various fields such as surveillance and search and rescue operations. Drones can be equipped with sensors and cameras, making them ideal for monitoring environment. In this section, we briefly discuss some important applications of drones in monitoring environments.

Disaster Management: Disasters are affecting different regions of the world every year. They are unstoppable events that are either natural or man-made, such as wildfire, earthquake, terrorist attacks, and floods. One of the major challenges faced by the rescue team during an enormous disaster is to find survivors and victims as early as possible and to take them out of the disaster area to ensure that they are not stuck under the destroyed area. In this regard, drones can help to detect people in disaster areas [6]. They can be equipped with sensors and camera to identify the precise location of survivors as early as possible. The data can be sent to the rescue team for further investigation and action.

Vegetation Management: Drones provide an important innovation in vegetation monitoring. By using the right sensors and an appropriate camera attached to it, it is possible to map the health of the crops by determining soil quality, humidity, and pollution in the area. The advantage of using drone-based system for vegetation monitoring is that unlike satellite images, drones can provide more information in relatively smaller areas. Moreover, the cost of using drones is much lower compared with manned flights, and therefore, it makes the technology more accessible.

Water Resource Management: Water management is one of the main issues in agriculture, in which new technologies such as drones can provide solutions. The use of drones in water management can help to provide solution on how to manage irrigation water and maximize its efficiency. For example, integration of UAV photogrammetry and image recognition technology can be used to solve the limitations of the existing measuring tools and techniques for water level measurements in the field [7].

1.2 Industrial-Based Applications

Drones or UAVs are playing a significant part in the industrial internet of things (IIoT) [8]. They can be valuable in industrial applications such as mining [9], oil and gas [10], and construction [11]. We briefly discuss some important aspects of these industrial applications in this section.

Mining Activities: Drones or UAVs can enhance security in applications related to mining activities with real-time information, such as latest surface surveys for enhanced blast patterns, quick and accurate pre- and post-blast information, and recognizing of misfire and wall damage. Moreover, drones can provide an effective approach to monitor stores and assist with area exploration as well as general management. In addition, miners can gain benefits from the use of drones in the design of roads and dumps, as they help them to find out more efficient approaches in terms of environmental impacts.

Oil and Gas: UAVs or drones have been deployed and used by several operators in oil and gas sector for various activities in difficult environments [10]. These activities include data collection, inspection, and exploration. Using inspection drones in oil and gas sector has several advantages over traditional inspection methods. For example, it eliminates major dangers to personnel involved in traditional inspection activities in dangerous environments. Moreover, a significant reduction in cost is achieved due to ease of access in difficult environments.

Construction: Aerial craft can be used in almost every stage of the engineering process, from planning to final construction. Helicopters and airplanes are already being used in civil engineering for different purposes such as mapping from a plane and producing marketing films for tourist destinations. Utilizing drones can significantly reduce the expense and time traditionally involved in various stages of the engineering process, such as construction of roadways and forest road, and coastal erosion.

The contribution of this study is that the proposed cost-effective framework deals with a cost minimization problem related to the optimal placement of drones which in turn monitors a set of static or dynamic targets. The minimization problem aims to reduce the number of drones in the environment while providing the maximum coverage, given a constant value of battery capacity. Moreover, the proposed framework can be integrated with Artificial Intelligence (AI) and deep learning for the problem of drone detection and tracking challenges [39]. For example, AI and deep learning can be used together with drones equipped with sensors as a promising solution in intrusion detection systems [40][41]. In addition, the study in [42] shows that Machine Learning (ML) algorithms can be applied in deployment of drone BSs in wireless networks to analyze the traffic pattern and estimate the traffic demand in the target system. Similarly, the authors in [43] utilize deep learning approaches for on-demand drone deployment in emergency and temporary conditions since the position of drones is a crucial factor that affects the available capacity to the data flows which is being served.

The remainder of this article is organized as follows. Section 2 presents the existing studies related to the use of UAVs in the IoT era. Problem description and the proposed framework are outlined in Section 3. Section 4 discusses the performance metrics, results, and findings of the study. Finally, Section 5 concludes this paper. A list of abbreviations together with their brief definitions used throughout the paper is provided in Table 1 to help the readers in understanding the abbreviated terms.

Table 1. List of Abbreviations

Abbreviated	**Name**
AED	Automated External Defibrillator
AI	Artificial Intelligence
CPMS	Canonical Particle Multi-path Swarm
CPS	Canonical Particle Swarm
DSP	Drone Scheduling Problem
ECA	Emission Control Area
FMPS	Fully Multi-path Particle Swarm
GPS	Global Positioning System
ICT	Information and Communication Technology
IIoT	Industrial Internet of Things
INS	Inertial Navigation System
IoT	Internet of Things
ITS	Intelligent Transport System
KF	Kalman Filter
LRBA	Lagrangian Relaxation-Based Approach
ML	Machine Learning
ODP	Optimal Drone Placement
OPA	Optimized Placement Approach
OS	Operating System
QoS	Quality of Service
TSP	Traveling Salesman Problem
UAV	Unmanned Aerial Vehicle
WBS	Wireless Base Station

2. Related Works

This section provides a review on existing studies related to use of drones and their deployment approaches in the IoT era. Recently, the use of UAVs or drones to control the emissions of sailing vessels has attracted too much attention due to its significant potential for performing regulations in Emission Control Areas (ECAs). In [12], the authors propose a drone scheduling problem (DSP) such that a group of planned tours is developed for drones to examine the vessels in ECAs. The dynamics of sailing vessels are modeled by utilizing a location function in real-time in a deterministic manner. They also propose a Lagrangian relaxation-based approach (LRBA), which is able to gain the best solution for the problem in large-scale cases. The results reveal that the proposed approach outperforms the commercial ones for the problem of up to 100 vessels. Drones have also been well utilized for military purposes [13-16]. For instance, the routing of a set of drones to destroy a determined group of targets that are prioritized differently is studied in [13]. The authors propose a two-phase approach that considers resolving a sub-problem related to target assignment for each drone in the initial phase. The second phase in this solution framework is to solve a travelling salesman problem (TSP) to obtain a routing plan. Similarly, the authors in [14] develop an integer-programming model for an environment where new targets may emerge dynamically. This model reassigns UAVs to the updated group of tasks regarding any changes in the battleground. In [15], the routing of UAVs is considered for military surveillance purposes, where UAVs gather information from targeted area using sensors. The proposed strategy chooses the sensors for each UAV by including payload capacity restrictions. Then, following these constraints, a group of UAVs is routed to develop a region-sharing approach by considering uncertainty on the data gained from observations. This strategy dynamically sends drones to gather information instead of focusing on a predesignated routing plan. The results of the study prove that the proposed approach is effective in a contemporary battleground where communications between UAVs and ground base stations are frequently blocked.

Besides military purposes, several studies consider the problem of routing drones in logistic delivery operations [17-19]. In this regard, drones assist trucks to deliver items to the customers who are located geographically. However, drones are often limited to carry only one package that makes the routing decision of the drones easier and enhance the operational efficiency [12]. For instance, a joint scheduling problem for trucks and drones is studied in [27]. In this study, drones are used to deliver packages to customers close to the storage, and trucks are responsible to deliver parcels far. The results reveal that, with such a delivery system, customers receive their orders faster. Moreover, it reduces cost of distributions as well as environmental impacts. Another similar problem is studied in [18]. In this study, trucks are permitted to carry UAVs in specific routes so that they can fly from the trucks and deliver parcels to people who are far from the storage. In [19], the authors prove that the potential improvement in delivery efficiency of the cooperation between drones and trucks depend on the speed of drones and the square root of the ratio of the speed of trucks.

UAVs or drones are increasingly proposed for medical use cases as well. For example, the study in [20] develops a new optimization model to help in the deployment of a network of automated external defibrillator (AED)-enabled medical drones to minimize the time it takes to reach to a patient's side. The proposed approach can optimally locate drones by considering the problem of backup coverage location with complementary coverage. At the same time, it improves backup coverage with insignificant loss of initial coverage.

In several studies, drones have been used for the tasks related to trajectory planning and task allocation [21, 22]. For example, in [21], the authors propose an automated surveillance system to track several mobile ground targets. The aim of this study is to reduce the total energy consumption and to find the exact location of the targets. The study in [22] proposes a system containing several operating drones and a control station. The drones receive control information from the control station and send their location information and the sensed parameters back to the control station. The results show the effectiveness of the proposed task allocation algorithm in terms of task completion.

Apart from the studies where drones are used for ideal trajectory planning problems, some studies have utilized drones to track different targets using various sensors. For example, in [23], an algorithm is proposed to track a mobile target in a cooperative manner using several drones equipped with cameras. The goal is to keep the mobile target in the position visible by cameras from various angles while achieving a low computational complexity. In addition, the authors in [24] investigated a similar problem by considering multiple criteria, such as the number of drones, the satisfaction of customers, and the total distance moved by the drones simultaneously. The objective is to detect the exact location of mobile targets using the sensors placed on the target.

Although the mentioned studies so far reveal the use of drones and their deployment approaches in the IoT era, but none of them consider the optimal drone placement (ODP) problem and the issues related to the target coverage. However, these issues are extensively investigated in the following studies [25-27]. For example, the optimal placement of a group of drones is considered in [26], with the assumption that a large number of drones are available to cover a group of mobile targets. The main objective of this study is to reduce the total amount of energy consumption. A similar study is presented in [27], where mobile targets are monitored by a group of drones that have restricted energy resources. The aim of this study is to reduce the number of required drones to monitor a piece of plane where the targets are moving. The authors mathematically present the problem under study by using mixed integer non-linear optimization models. In addition, heuristic procedures according to restricted mixed integer-programming formulation are defined for the problem. Finally, the behavior of the proposed model is assessed and a comparison is provided between the proposed model and the mixed integer-programming-based heuristic models in terms of efficiency and effectiveness. In [25], the authors propose a mathematical model to formulate the ODP problem. They provide an improved model that considers the energy of each drone, and design an ideal approach to solve the placement problem of static or mobile drones. Using two low-complexity centralized algorithms, samples of the mentioned problem with more than 50 targets and a large number of possible locations for the drones can be solved.

Although these studies tried to solve the ODP problem with the reduced amount of energy consumption, but they did not attempt to provide the maximum coverage for the drones while minimizing the total number of drones in monitoring the environment which is considered in this study.

In [32], the authors examine and simulate real time Inertial Navigation System (INS) and Global Positioning System (GPS) in UAV navigation using a two-level Kalman Filter (KF). The proposed approach is based on predicting the error in position of the INS and then removing it from its corresponding position besides the second level of applied KF for the entire integrated GPS/INS errors. The results obtained show that the KF-based module is able to decrease the INS position error and prevent its growth even in the long-term period. The study in [33] introduces an optimized data delivery framework called Canonical Particle Swarm (CPS) for multimedia delivery using drones in the 5G/IoT era. In the proposed framework, multi-swarm strategy is utilized to specify the optimal direction while carrying out a multi-path routing. The results show the performance improvement of the proposed method compared to other ordinary optimization approaches such as Canonical Particle Multi-path Swarm (CPMS) and Fully Multi-path Particle Swarm (FMPS).

In [34], the authors present a study which aims to find the optimal locations for static drones in a given area in order to maximize the coverage. The algorithm solves the ODP problem for both clustered and uniformly targets. The results show the effectiveness of the proposed approach in solving the placement problems of drones. However, the approach does not consider the mobile targets in the area.

The authors in [35] use an algorithm based on gradient projection in order to find the optimal placement of a single drone in case it can be used as aerial Wireless Base Station (WBS) when cellular networks are out of service. They consider the uplink scenario as a constraint and find an optimal location for the drone in a way to maximize the sum of durations of the time of uplink transmissions. A similar study in [36] presents an algorithm to optimally locate drone BS in an area with various target densities. The authors aim to minimize the number of drones and their 3D placement in a way that all the users are served.

Another study on 3D deployment of drone BSs is presented in [37]. The authors propose a framework to maximize the number of covered users with various Quality of Service (QoS) requirements. They model the problem as a placement problem with multiple circles and propose an algorithm that uses an exhaustive search in a closed region over a 1D parameter. In addition, the authors propose the maximal weighted area algorithm to deal with the placement problem. Such use cases are important due to the growth of data traffic caused by multimedia applications [38].

3. Proposed Methodology

One of the major drawbacks of drones is their limited range [28], which is due to the capacity of the battery. Another challenging issue regarding the usage of drones is related to their high price. Therefore, there is a need to optimize the number and location of drones to have full coverage of an area. In this regard, we propose a method called optimized placement approach (OPA) to minimize the total number of drones required while providing maximum coverage. This in turn leads to reduction in cost.

3.1 Optimized Placement Approach

The relationship between the drone's height and the coverage area of the target can be formulated by $A = \pi(R^2 - h^2)$ where h is the height of the drone, and A and R are the drone's coverage area and the radius of the drone's wireless transmitter respectively. Clearly $A = \pi R^2$ when $h = 0$. In our model, we assume that there are N drones in the area in which they can fly to a maximum height of h_{max} and minimum height of h_{min} maintaining a particular coverage radius [25]. We assume that there is a location (x, y, z) that each drone can be placed in the area.

Please note that deploying drones to cover targets is not a simple problem. The deployment strategy should reduce the overall cost by minimizing the number of drones required to control a target. They should be placed in a way to cover all the targets while having minimum overlapped coverage between drones. Moreover, there should be high quality wireless communications between the drones and the ground targets which can be achieved by reducing the altitude of the drones. In addition, multi-hop connectivity between the drones and a BS can be provided using air-to-air communications. Therefore, connectivity, full coverage of the targets and the quality of the coverage are the main objectives and constraints of our problem.

Let D denotes a group of available drones and T represents the group of targets to be monitored. The objective function is to minimize the total number of required drones for monitoring the environment. Assume that each target is determined by the values (x, y, z), where x, y, and z signify length, width, and height of the target, respectively. Therefore, given a drone d, it is located at a coordinate (x, y, z) with a target T to be monitored. It is possible to define the distance between d and T_i when z = 0 as follows [31]:

$$U_{t_i}^{x_d y_d} = \sqrt{\left(x_{t_i} - x_d\right)^2 + \left(y_{t_i} - y_d\right)^2} \tag{1}$$

Drones have a visibility of θ, which is signified by a disk on the plane with radius r^z depending on z_d. The drone visibility is also dependent on the angle of camera lens. Moreover, the position where each drone $d \in D$ should be located (x_d, y_d, z_d), and the target $t_i \in T$ monitored by the drone should be decided. Therefore, the first decision variables are defined as follows:

$$\delta_{xyz}^{d} = \begin{cases} 1 & \text{if } d \text{ is located at coordinate} \left(x, y, z\right) \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

$$\gamma_{t_i}^{d} = \begin{cases} 1 & \text{if taret } t_i \text{ is observed by drone } d \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

The goal is to carefully control and watch all the targets with minimum one UAV to minimize the required number of drones as well as total energy consumption which will be formulated in section 3.2. Furthermore, according to [25][27][30] the energy consumption of each drone can be formulated as follows:

$$E = \left(\beta + \alpha k\right) t + P_{max} \left(K / S\right) \tag{4}$$

where β is the minimum power for the drone required to stay in the air and α is a motor speed multiplier. α and β are both dependent on the weight of the drone, and the features of the motor it is using. P_{max}, S, and t are maximum power of the motor, speed, and the operating time, respectively. The term αk indicates the relationship between the height and power, and P_{max} *(K/S)* is the power required to move up to height *K* with speed *S*. The objective function is to minimize the total number of required drones for monitoring the environment, which can be formulated as follows:

$$\text{Min } f(\delta)\ s.t \sum_{(x,y,z)} \delta_{xyz}^{d} \leq 1 \forall \quad d \in D \tag{5}$$

$$\gamma_{t_i}^{d} \leq \sum_{(x,y,z)} \delta_{xyz}^{d} \left(\frac{r^{z_d}}{D_{t_i}^{dxy}} \right) \quad \forall d \in D,\ t_i \in T \tag{6}$$

3.2 Equations of the Drone's Location

The flying zone for the drone is represented by $Z = [Z_{min}, Z_{max}]$. This is the area that is parallel to the plane containing the targets. Detection of the target above Z_{max} is not possible, and the drones are not permitted to fly above this threshold in the region. In addition, drones cannot fly below Z_{min}. The flying zone is presented by a rectangle of length X_{max} and width Y_{max} such that

$$\sum_{d \in D} \gamma_{t_i}^{d} \geq 1 \quad \forall t_i \in T \tag{7}$$

When the drones fly, they need to observe the target for a specified amount of time. Additionally, the target can move in the region, particularly a time window $\left[\tau_{min}^{t_i}, \tau_{max}^{t_i}\right]$ is associated with each target $t_i \in T$, meaning that at the beginning the target t_i is placed at the point of coordinate, and it has been detected in the time range specified by the time window. If the target is moving to catch mobility in the system, a sequence coordinate C_i is associated with each target. According to [26], it is assumed that:

$$|C_i| = \left\lceil \frac{\tau_{max}^{t_i} - \tau_{min}^{t_i}}{\Delta \tau} \right\rceil \tag{8}$$

where $\Delta\tau$ represents the time interval such that a new location of the target t_i is obtained. Considering all the constraints and objectives discussed earlier, the equations to minimize the number of required drones and the total energy consumption can be formulated as follows:

$$f(\delta) = N * \sum_{(x,y,z)} \sum_{d \in D} \delta_{xyz}^{d} t \tag{9}$$

$$f(\delta) = A - N * \sum_{d \in D} \delta_{xyz}^{d} * A_i \tag{10}$$

Where A is the entire area to be monitored and N and A_i are the number of drones and the area monitored by the i^{th} drone respectively.

$$E = N * (\beta \sum_{(x,y,z)} \sum_{d \in D} \delta_{xyz}^{d} t + a \sum_{(x,y,z)} \sum_{d \in D} Z \delta_{xyz}^{d} + \frac{P_{max}}{S} \sum_{(x,y,z)} \sum_{d \in D} Z \delta_{xyz}^{d}) \tag{11}$$

4. Performance Evaluation and Results

In this section, to assess our proposed model, we discuss the performance metric and parameters as well as the results obtained by simulation.

4.1 Simulation Setup

Equations (1)–(10) in Section 3 are aimed to minimize the number of drones. The simulation has been implemented in Octave programming language, namely GNU 4.4.1 [29] which is a high-level scientific programming language primarily intended for numerical computations. Octave is an important open-source and free software tool used in robotics which is equivalent to Matlab. Our simulation script was executed on a device with Windows 8 Operating System (OS). The device has the following specifications: Intel(R) Atom(TM) CPU Z2760 @ 1.80 GHz, 1,800 MHz, 2 Core(s), 4 Logical Processor(s). The usage of RAM was low, and the computation time was from 4 to 6 s. There are a couple of assumptions that were made during the simulation phase. First, the battery capacity is not subjected to optimization, that is, the optimum value for battery capacity corresponding to the minimum number of drones are determined through trial and error. This is because various applications have different requirements which may affect the battery capacity. Therefore, through the trial and error, we determine the optimum value for the battery capacity of the drones. Second, each drone covers an area that is a square of 1 km^2. The reason for choosing such a large coverage area for the drones is that we are targeting a large-scale scenario such as street coverage in smart cities. Finally, for simplicity purposes, the communication range between drones is considered as circular disks.

4.2 Performance Metrics and Parameters

To assess the proposed framework, the following performance metric is considered in the script.

Target Coverage: This is the coverage area of drones while flying over a target. The metric is evaluated while varying the following parameters:

Energy (E): It represents the initial capacity of the drone's battery.

Visibility angle (θ): It is the opening of the drone visibility range.

Horizontal Energy Consumption (γ): This is the energy consumed due to the horizontal movement of the drone.

Vertical Energy Consumption (α): It represents the energy consumed due to the vertical movement of the drone.

Number of Targets (nt): It represents the number of targets to be monitored by the drones.

Please note that there are also some important parameters such as delay which can affect the critical applications of the UAVs. For example, the average experienced delay in the system may change if the height of the drone changes. In this regards, if the height of the drone increases, the delay may increase too. This is due to the increase of coverage in the space that permits less hops between the target and the final destination. Another critical communication metric is the network throughput which can be defined as the amount of useful works such that connected drones can carry out per the unit of time in terms of bytes that have been delivered successfully to the base station. If the number of drones increases, the network throughput increases too. This is clear when there are more drones available, there will be more routes available towards the base station. This in turn causes improvement in the data delivery. However, by increasing the number of drones, the total energy consumption of the network increases as well. Therefore, it is important to find the optimal number of required drones for monitoring an area in order to have an energy-efficient system.

4.3 Results and Discussions

In this section, we discuss the results obtained from the simulation tool implemented to evaluate the performance of the proposed framework. During the simulation, we considered two phases: static and dynamic targets.

4.3.1 Static Targets

Static targets have fixed positions and do not change their locations. We considered two situations regarding static targets. First, given a fixed number of targets ($nt = 100$), the results for the optimal solution (e.g. minimum number of drones) are obtained as follows. Figure 1 shows a scenario where the drones, which are flying away either horizontally or vertically or both, have a narrower visibility range than the ones close to the (0, 0) coordinates. The number of drones is initially 23 drones. If we decrease the energy consumption of flying horizontally to $\gamma = 2$ with less battery capacity as in Figure 2, it can be seen that drones flying to the right and to the top right of Figure 2 are covering more targets due to flying further. Doing the same steps of decreasing energy cost of moving horizontally and the battery capacity makes the drones fly further and higher. Therefore, a bigger visibility range is achieved as shown in Figure 3.

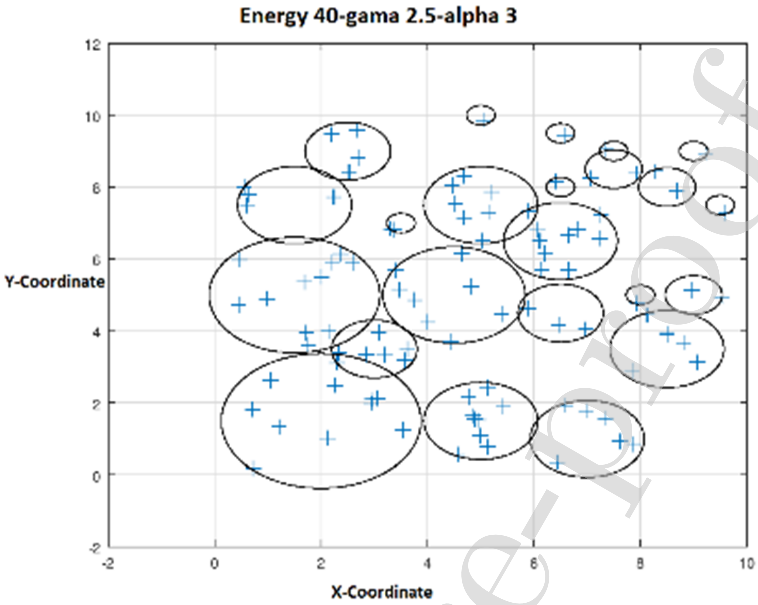

Figure 1 - Energy = 40, gamma = 2.5, alpha = 3.

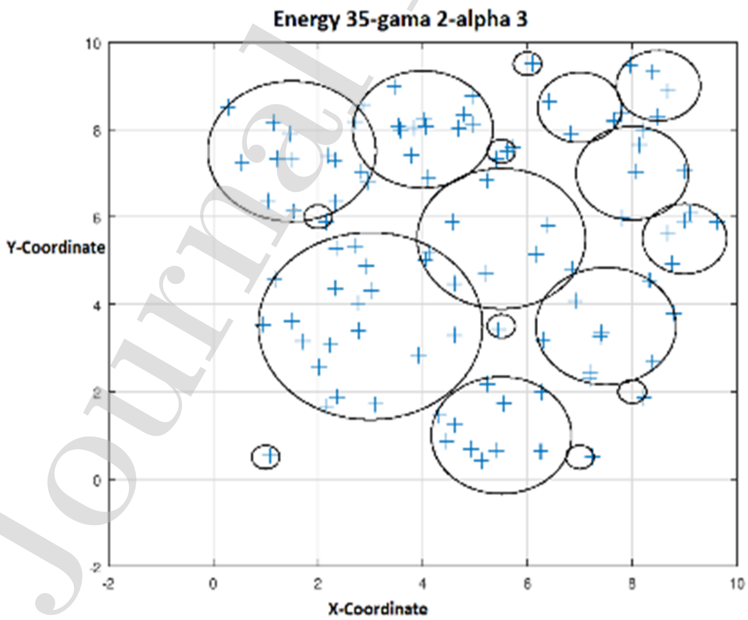

Figure 2 - Energy = 35, gamma = 2, alpha = 3.

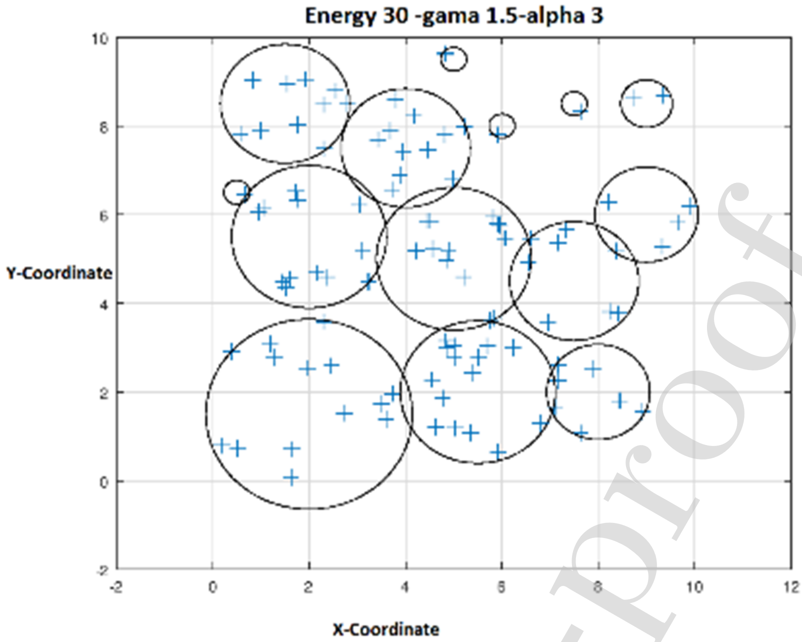

Figure 3 - Energy = 30, gamma = 1.5, alpha = 3.

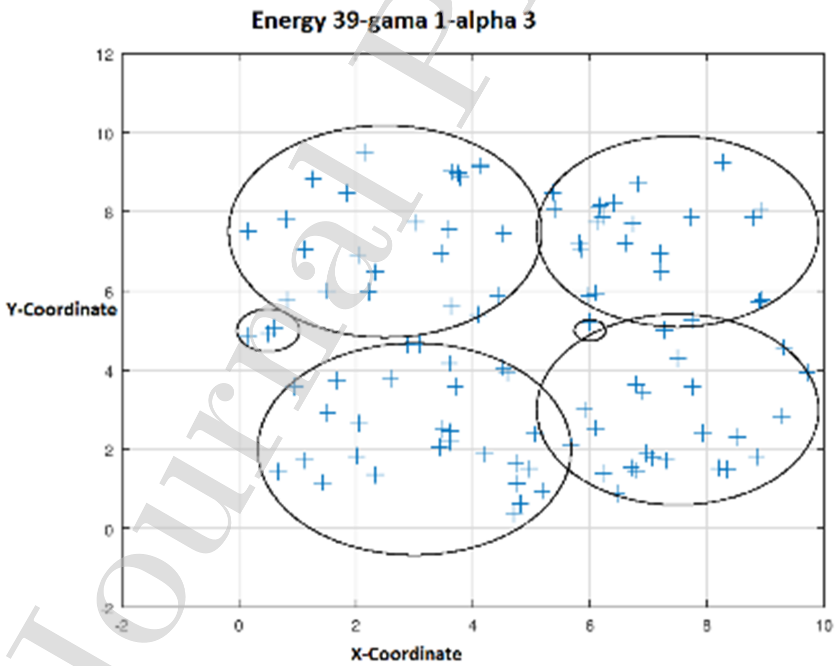

Figure 4 - Energy = 39, gamma = 1, alpha = 3.

More optimal results can be reached by increasing the battery capacity while maintaining the cost of flying horizontally and vertically. Figure 4 shows the least number of drones with wider visibility range than the ones on Figure 5, where the drones' visibility range is smaller. Drones that are flying further away from the hub (zero coordinates) have less visibility range by the time they reach their destination. This is because traveling further diagonally consumes more energy than flying close to the hubs (due to the short distance traveled). Therefore, this leads them to decrease their elevation and their visibilities simultaneously.

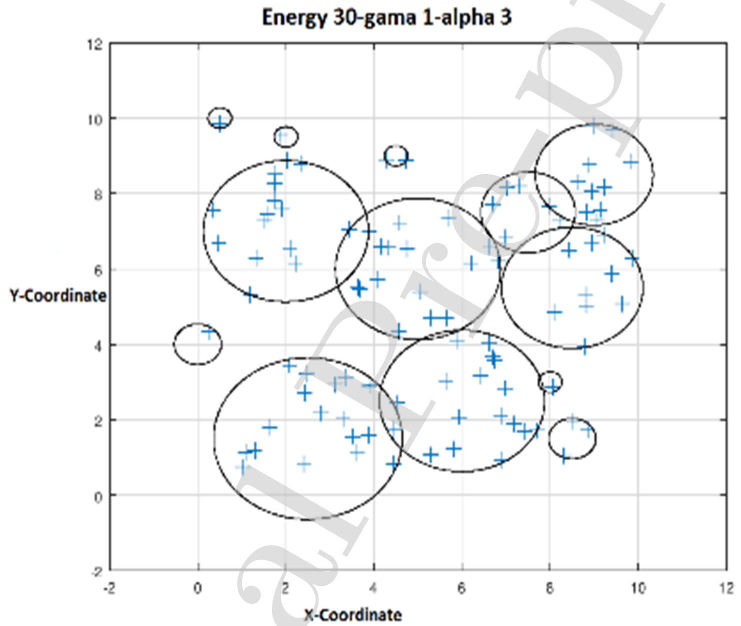

Figure 5 - Energy = 30, gamma = 1, alpha = 3.

In the second scenario regarding static targets, we changed the number of targets (*nt*) and kept the following energy-related parameters constant; $E = 40$, gamma = 2, and alpha = 4. We then observed the changes in behavior. Figures 6 – 10 represent target coverage by drones with respect to the number of drones. Figure 6 shows three targets in different locations, since they are away from each other; three drones are needed to cover them. If the number of targets is *x,* then the number of drones can have a value ranging between a minimum of 1 and a maximum of x. As the number of targets increases, the number of drones increases as seen in Figures 7 – 10.

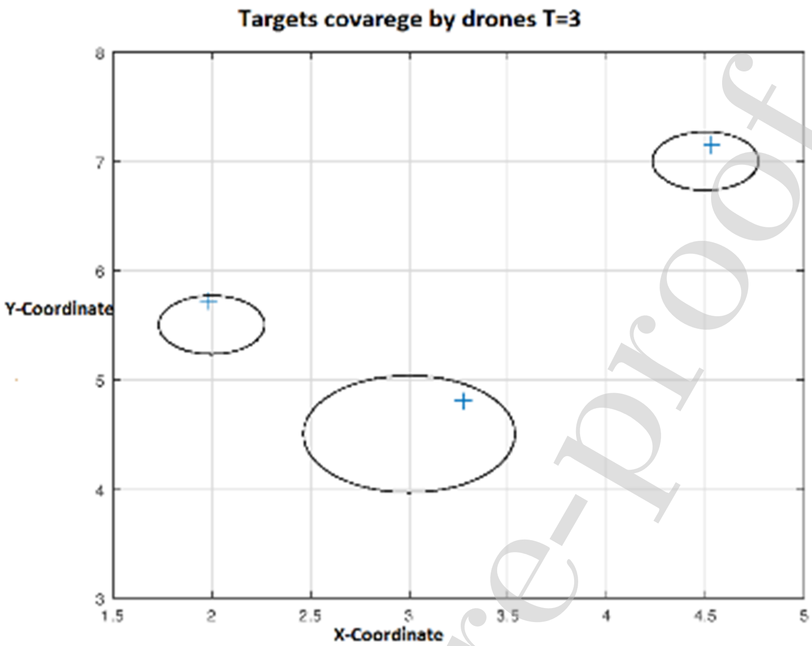

Figure 6 - Targets coverage nt = 3.

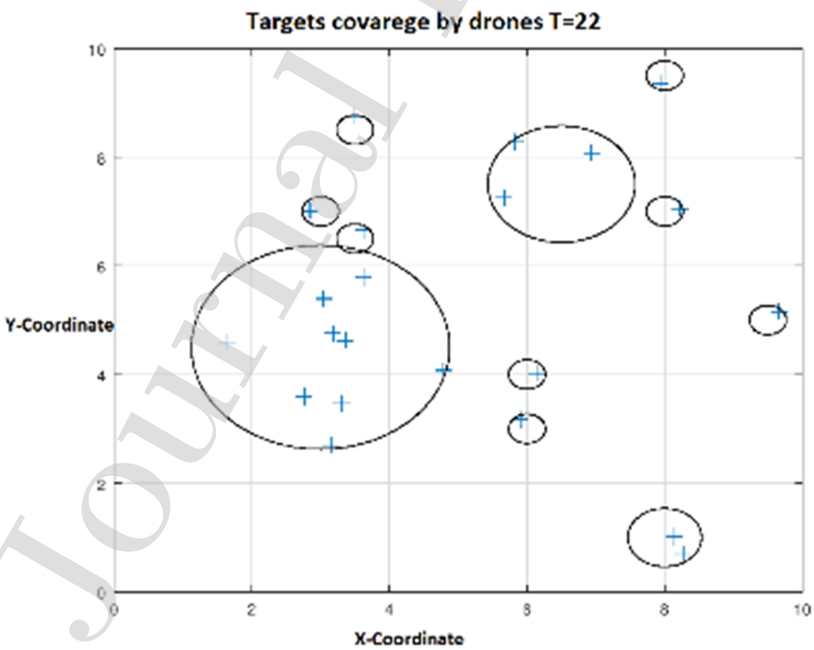

Figure 7 - Targets coverage nt = 22.

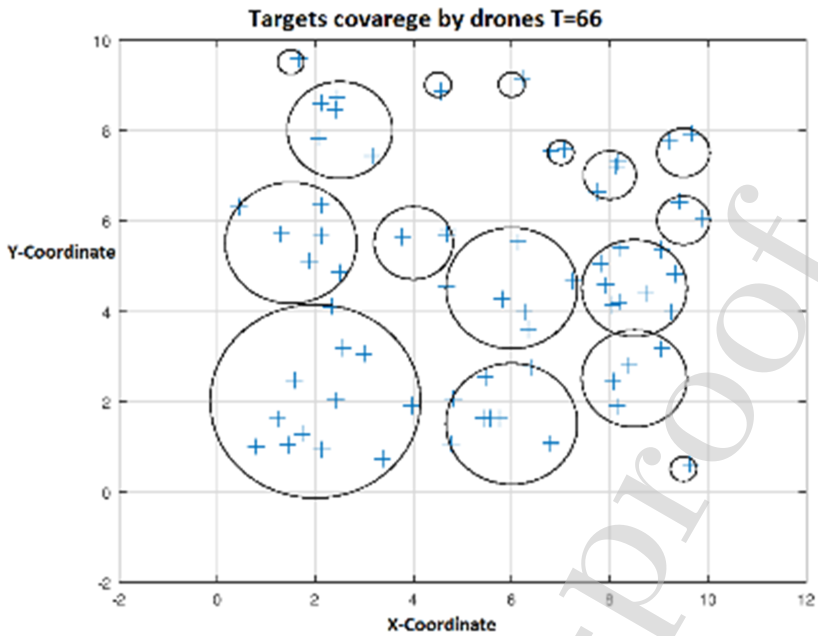

Figure 8 - Targets coverage nt = 66.

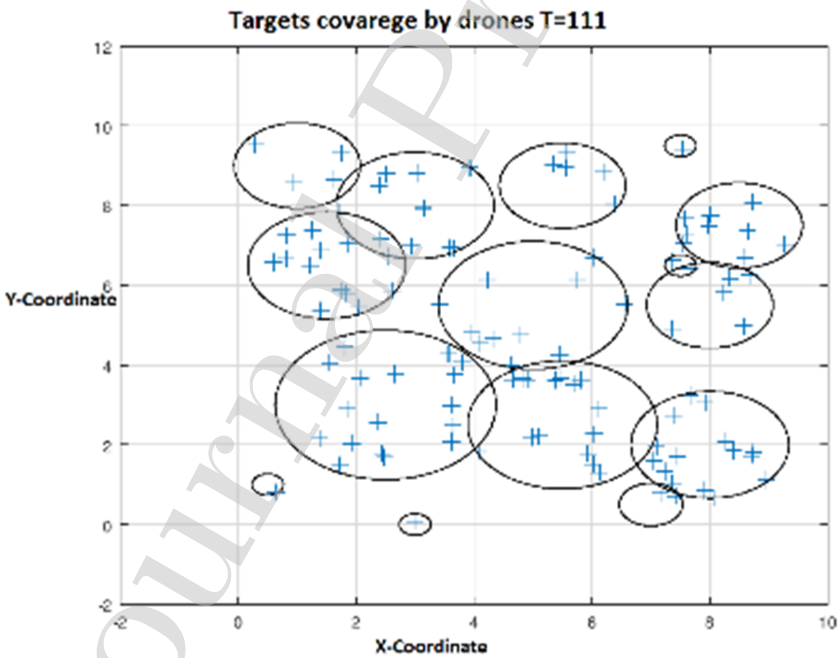

Figure 9 - Targets coverage nt = 111.

Figure 11 shows the number of drones with respect to the number of targets. As it is expected, the number of drones needed to monitor a given number of targets increases gradually. However, this is only true, until a certain number of targets. This number of targets requires the highest number of drones to be monitored. It can be thought to cover several varying regions across the total area being monitored. Later, if the number of targets is further increased, the number of drones does not increase.

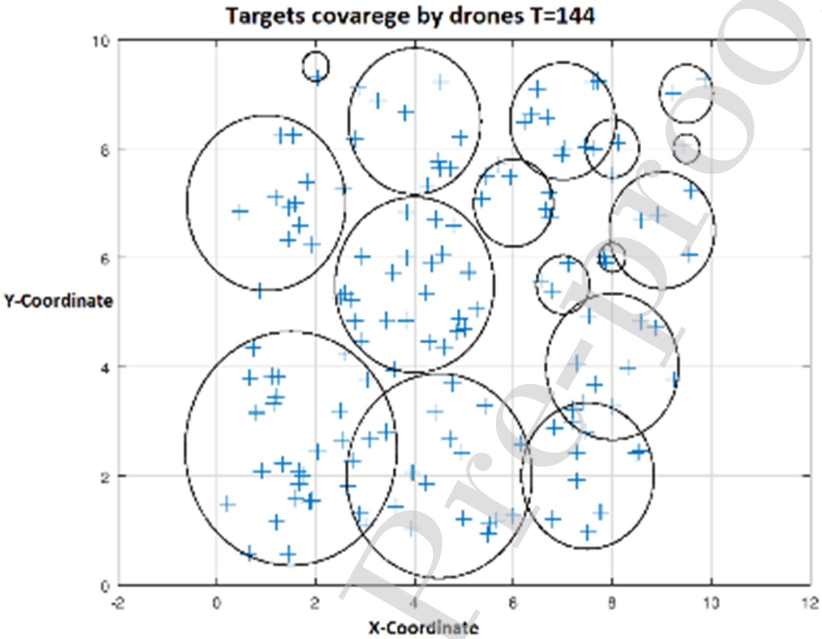

Figure 10 - Targets coverage nt = 144.

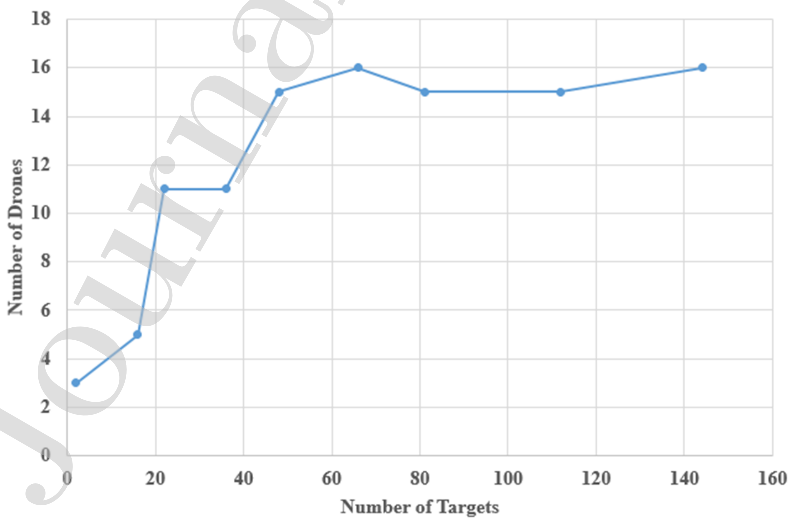

Figure 11 - The relationship between the number of drones and targets.

4.3.2 Dynamic Targets

So far, we have assumed that the targets are static (not moving). However, in this scenario, we assume that the targets are capable of moving throughout the time they are being monitored. To display this effect in the simulation, the *seqLength* (S_L) and *walkArea* (W_A) parameters change. As explained earlier, S_L is the number of time intervals in which the target moves (i.e. how many times the target will move), and W_A is how far the target moves within every time interval. For example, if S_L =2 and W_A =3, then each target will move randomly twice, each with three steps. We set the energy-related parameters as E = 40, gamma = 2, and alpha = 4 to observe the changes. The script is written in such a way that if the target is static it draws a plus (+) sign, otherwise, it draws a minus (−) sign, and displays the trajectories of movement of the drones. Figure 12 shows static and non-moving targets, whereas in Figure 13, the targets are moving slightly. The visibility range of drones is slightly overlapping. This is due to the fact that the drones are trying to cover the moving targets.

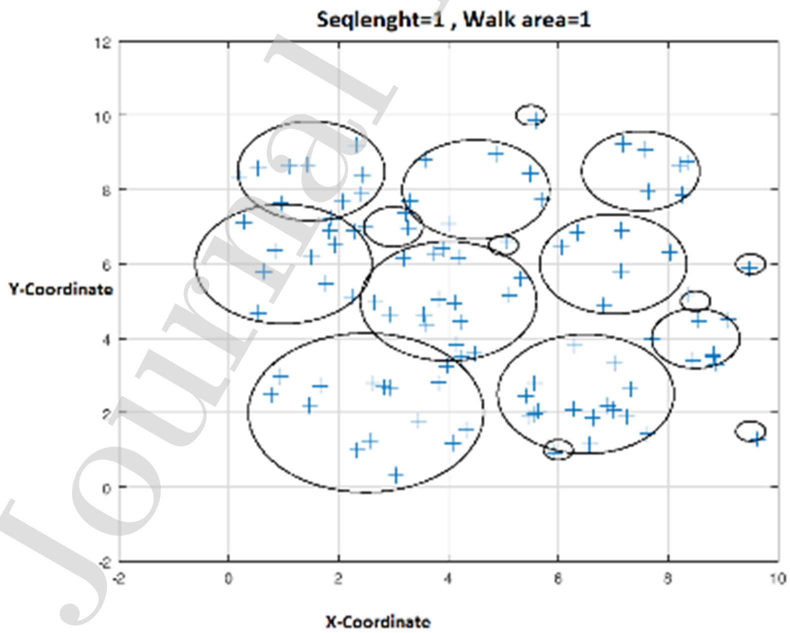

Figure 12 - Targets coverage with S_L = 1, W_A = 1.

In Figure 14, each target moved five times, each time with five steps, where each colored segment shows the trajectory of a certain target. As it can be seen in Figure 14, the targets are moving a lot more than the previous ones. Therefore, the overlapping region between the drones' visibility range is higher. The reason for this overlapping is the long trajectories of the targets, where they get too close to each other.

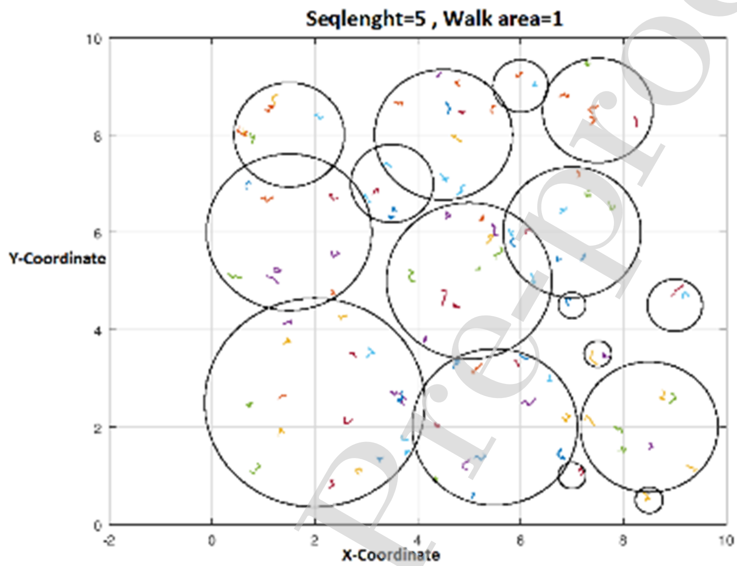

Figure 13 - Targets coverage with S_L=5, W_A = 1.

Observing the change in the target's behavior and the number of targets with respect to S_L and W_A parameters, we notice that the longer path the trajectory target takes, the closer the targets get to each other. Therefore, less number of drones is needed to cover them. Figure 15 shows how the number of drones decreases as the trajectory length increases. The trajectory length (T_J) was calculated using the following equation:

$$T_J = W_A * S_L \tag{12}$$

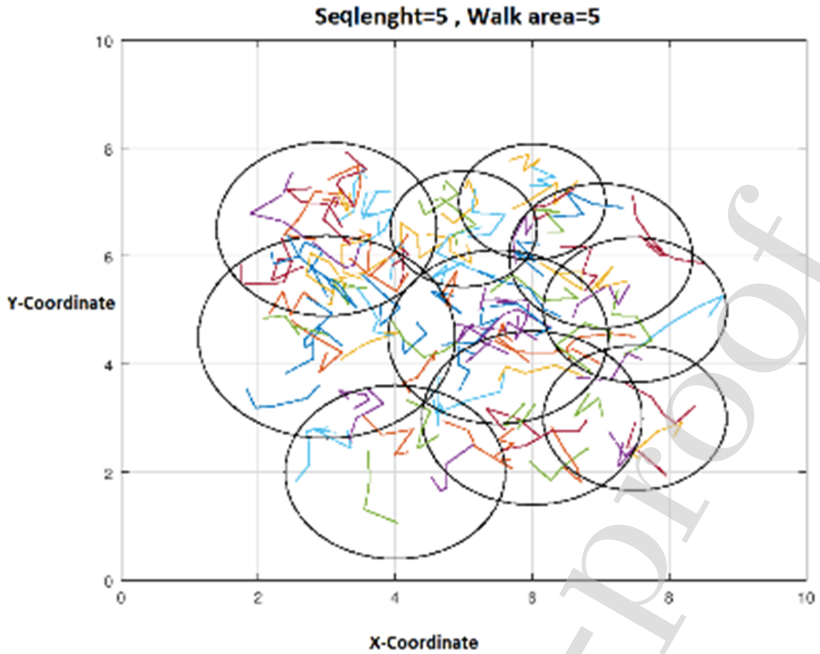

Figure 14 - Targets coverage with $S_L = 5$, $W_A = 5$.

As it can be seen in Figure 15, the curve clearly displays the inverse relationship between the number of drones and the corresponding lengths of the trajectories of targets. This is clearly observed as the highest number of drones corresponds to the lowest trajectory length and vice versa.

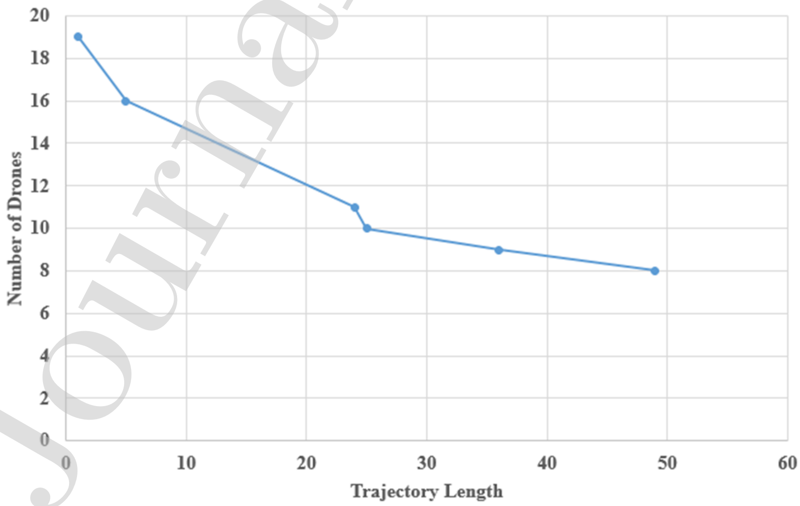

Figure 15 - The relationship between trajectory length and the number of drones.

5. Conclusion

In this study, a cost minimization problem is considered which is related to the optimal placement of drones to monitor a set of static or dynamic targets. Our minimization problem aims to minimize the number of drones, given a constant value of battery capacity. The problem stated earlier is formulated, and the mathematical models were provided accordingly. The simulation results obtained from different variations in changing the parameters reveal that increasing the battery capacity leads to an increase in the drone's visibility range, and thus, a decrease in the number of drones. This effectively provides a better solution for our minimization problem. Moreover, when dynamic targets are considered, moving with higher W_A leads to targets ending up in locations close to each other. In actuality, almost an inversely proportional linear relation exists, as can be seen in Figure 15. Therefore, the drones' visibility areas will be overlapping, which may cause a number of drones to be considered as redundant, leading to a smaller number of drones. Finally, there exists a limit where the number of drones no longer proportionally increases in relation to the number of targets. This is because the limit exhibits a case where the targets are distributed across a large number of different regions in the area monitored, rendering a further increase to the targets that does not require an increase in the number of drones needed to monitor them.

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