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RESEARCH ARTICLE

A Safety System for Maximizing Operated UAVs Capacity Under Regulation Constraints

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ABSTRACT Recently, the emergence of Unmanned Aerial Vehicles (UAVs) has garnered significant attention due to their widespread applications, such as surveillance, mapping, reconnaissance, as well as commercial delivery, and photography. Despite the tremendous applications of UAVs, there are potential risks associated with drones that may impact flight safety. For instance, launching and releasing drones near airfields can pose serious threats to flight safety. Another challenge is the flying altitude. Flying at high altitudes might cause a collision with other aircraft, and flying at low altitudes can also pose a significant threat due to obstacles in the environment. Various regulations, such as airspace restrictions, flight altitude limits, and safety requirements, can limit the number of UAVs operating in a particular area. This, in turn, makes it challenging to specify the number of UAVs that can operate safely. To address these challenges, we propose an optimization strategy to maximize the number of UAVs that can operate while adhering to regulatory constraints. The problem is formulated and solved using an improved version of a population-based meta-heuristic, IPSO. In the proposed approach, we consider two distinct objective functions. The first one is the local objective function, which aims to minimize the energy consumption of the generated path by IPSO. This objective function is crucial in ensuring that the generated path is energy-efficient. The second objective function is the global objective function of the proposed approach, and aims to maximize the number of UAVs that can operate in a specific area. The proposed approach studies the impact of regulations such as obstacles and flying altitude on a region capacity. The results show that the proposed approach successfully increases the the region capacity, i.e., number of UAVs, to the maximum possible while ensuring safety and regulatory constraints.

INDEX TERMS Regulation constraints, region capacity, UAVs formation, path planning, IPSO.

I. INTRODUCTION

Due to advancements in science and technology, drones have become increasingly diverse and widely used in various applications, including monitoring traffic, tracking environmental conditions, and delivering goods [1]. They offer great flexibility and can work effectively in various locations and situations that humans can't access [2], [3], [4]. Drones can also fly very close to target objects, enabling them to provide more precise measurements and perform more targeted actions. These features make drones an ideal choice and viable solution to address issues for smart city applications that require faster and more efficient delivery services [5], [6], [7]. With their numerous advantages, drones are already being employed in smart cities to enhance urban life by documenting accident scenes, and monitoring construction sites [8], [9]. The use of drones for everyday consumer services is growing and becoming a reality [10].

Despite the tremendous applications of UAVs, there are also potential risks associated with drones that may impact national defense, security, flight safety. The risk of UAVs accidents with other members in the sky increases as the

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number of drones increases. This poses a threat not only to civil aviation regarding security and infrastructure but also to traffic safety. Nowadays, there have been several high-profile incidents involving drones [11]. Additionally, there have been numerous instances where drones have come dangerously close to colliding with airplanes. According to data collected by the FAA in 2015, pilots reported over 700 near-miss incidents involving drones between January and August of that year [12]. Furthermore, a study by [13] analyzed a dataset of drone accidents and incidents in Australia and found that two major causes were equipment malfunctions and a lack of coordination between aerial activities. With the growing interest in drones among commercial entities, it is crucial to prioritize safety for people, properties, and other airspace users such as helicopters during drone operations. Launching and releasing drones near airfields, known as no-fly zones (NFZs), where aircraft operation can pose serious threats to flight safety, especially if small drones are launched during the takeoff or landing of aircraft. The airspace surrounding airports is heavily monitored and regulated to protect the safety of manned flights, and unauthorized drone operations in these areas can create a significant risk of collisions or other safety hazards. Many countries have implemented strict rules and guidelines for UAV flights near airports, which could involve restricted zones, altitude limitations, and other restrictions. As a result, it's crucial to verify the local regulations and airspace limitations ahead of flying UAVs and to avoid flying close to airports or within restricted airspace. Figure 1 shows the buildings and other environmental constructions in the urban space with different rules. For the urban dangerous obstacles in the global map environment.

Additionally, drones with weights ranging from a few hundred grams to several tens of kilograms and the ability to fly at altitudes from one hundred meters to thousands of meters can pose a danger to people, vehicles, and infrastructure in case of an incident.

It has to be stressed that the safety of UAV operations can be significantly impacted by the altitude at which they operate, particularly with regard to collision avoidance. UAVs flying at higher altitudes are at a greater risk of colliding with other aircraft or obstacles, especially in non-segregated airspace. One of the primary concerns associated with UAVs operating at higher altitudes is the increased likelihood of collisions with other aircraft and can pose a significant threat to commercial aviation, especially if they enter controlled airspace that are considered NFZs. Also, flying at low altitude can pose a significant threat due to obstacles filled the environment.

Moreover, the increasing number of UAVs in the airspace may lead to congestion, making it difficult to manage and regulate UAV traffic. More importantly, the intra collision with other UAVs represent another challenge to UAVs safety. The risk of accidents increases as the number of UAVs in operation area increases. Therefore, it is crucial to establish a robust system that ensures UAVs safety by applying regulation constraints and guarantees operation safety of UAVs in a given region.

Another challenge of UAV is its limited battery life which is a significant limitation for unmanned aerial vehicles (UAVs), which commonly rely on rechargeable batteries for power. To increase a UAV's flight time, the UAV should be endowed with energy efficient collision-free path generator that can generate flight paths with minimum energy consumption.

To cope with the above challenges, we propose a safety system for UAVs that determines the maximum region capacity, i.e., maximum number of UAVs that can operate safely within a given region, while fulfilling with regulation and terrain constraints. The proposed approach starts with a certain number of UAVs and incrementally increases the number of UAVs until a collision is detected. An optimization technique is applied in our proposed system in which regulation, terrain, and UAVs constraints are considered and maximum allowable flying UAVs is achieved. The system receives regulation constraints such as maximum altitude, speed, as well as region constraints such as obstacles, threats, and NFZs, and generates a maximum number of UAVs with their energy-efficient paths, that can operate in the specified region. The IPSO approach is applied to obtain a collision free paths for all UAVs. We propose two objective functions, namely, local objective function, and global objective function. The local objective function is utilized within IPSO to generate a minimum energy paths for all UAVs, while the global objective function aims to maximize the number of UAVs that can operate in a specific region. The system studies different altitudes and different obstacles sizes.

The contribution of this work can be summarized as follow:

1) We propose a safety system for UAVs that determines maximum number of UAVs that can operate safely within a given region, while fulfilling with regulation and terrain constraints.
2) The problem is formulated as a maximization optimization problem with the aim of achieving maximum allowable flying UAVs and consider regulation, terrain, and UAVs constraints such as maximum altitude, speed, as well as region constraints such as obstacles, threats, and NFZs.
3) The IPSO approach is applied to obtain a collision free paths for all UAVs. We propose two objective functions, namely, local objective function, and global objective function. The local objective function is utilized within IPSO to generate a minimum energy paths for all UAVs, while the global objective function aims to maximize the number of UAVs that can operate in a specific region.
4) The system studies different altitudes and different obstacles sizes.

The rest of this paper is organized as follows: section II gives the literature review. In section III, improved particle

FIGURE 1. Example map of urban 3D environment modeling.

swarm optimization is discussed. The UAVs path planning description is illustrated in section IV which includes path representation, and obstacles modelling. Section V discusses the System model description for maximizing region capacity which includes design of constraint, objective functions, problem formulation, and optimization algorithm of the System model. Section VI presents simulation results and the corresponding analysis. The work is finally concluded in Section VII.

II. LITERATURE REVIEW

As science and technology have advanced, drones have become increasingly diverse and widely utilized across multiple fields, providing significant socioeconomic advantages such as enhancing agriculture [14], [15], and reducing labor costs. However, there are also potential hazards associated with drones that could impact flight safety, and social order and safety. The state of the art can be grouped into three groups: UAV safety and privacy, regulation and constraints, and UAV management.

A. UAV SAFETY AND PRIVACY

The safety of flight can be compromised by launching UAVs or drones near airfields where civil and military aircraft operate, particularly if small drones are launched during takeoff or landing, as this could result in a catastrophic aviation disaster.

The use of drones poses a threat to social security, order, and safety due to their weight, which can range from a few hundred grams to several tens of kilograms, and their ability to fly at altitudes ranging from one hundred meters to thousands of meters. In the event of an incident, drones could endanger people, vehicles, and infrastructure [16].

In [17], the authors conducted a comparison of safety and privacy regulations for UAVs across several regions and countries. Specifically, they collected and analyzed information regarding regulatory frameworks and guidelines from different regions including the United States, Europe, China, and Australia. Through this analysis, the study involved the variations and similarities in safety and privacy regulations among the regions and identified forbidden areas in the existing regulatory systems.

The work in [18] explained a reference scenario and an adversarial model and examined previously published privacy-preserving schemes related to Remote ID. These schemes were categorized by attributes such as drone/operator identity privacy, location privacy, compliance with Remote ID requirements, and communication technology.

B. REGULATION AND CONSTRAINT

Several studies have addressed the regulation of drones and their impact on behavioral privacy [19], regulatory compliance [20], user perspectives, public safety, data protection, and ethics. Furthermore, numerous researchers have focused on the primary factors that affect drone policy compliance and the safe integration of drones into the national airspace system. The study conducted by Henderson investigated the views of New Zealand drone users on safety regulations for drones [21]. The study indicated that the current regulatory system was appropriate, with only a minority advocating for stricter or less strict regulations. The work in [18] also provided a summary of the current regulations for Remote ID, which was used to track and identify drones in specific airspace systems.

Fedorko conducted a research study on the lawful use of drones in the Slovak Republic [22]. The rise in drone usage is expected to create a new competitive environment for operating companies and cooperative enterprises. However, the existing legislation pertaining to drone usage does not adequately address this challenge due to the flexible legal use of drones, including employee monitoring and document delivery.

Stöcker et al. outlined the key aspects of drone regulations [23]. Their study comprised a comprehensive review of global regulations and primary criteria. By analyzing the data and applying appropriate analysis techniques, the authors provided an overview of the past, present, and future trends in drone regulations. In doing so, they examined and discussed the legal frameworks for operating drones with regard to privacy, data protection, and public safety.

In [10], the paper examined how drone operation in an urban environment was managed and regulated through a case study in a Brazilian city where drones were utilized for aerial photography and surveys. The authors investigated the regulatory framework for drone operations in Brazil and the difficulties associated with their use in urban settings. They underlined the importance of developing regulations that stroke a balance between the benefits of drone technology and the need to safeguard public safety and privacy. The study suggested the use of geofencing and other technological solutions as methods of enforcing regulations and reducing potential risks associated with drone operations in urban areas.

The work in [24] investigated the regulations governing the on-road testing of connected and automated vehicles (CAVs) and evaluated the potential for achieving global safety harmonization. The authors examined the regulatory structures in different countries, such as the United States, China, and Germany, and analyzed the differences and similarities among them. The study highlighted the difficulties in achieving global safety harmonization due to variations in regulatory approaches and the absence of a common set of standards. The authors put forward a framework for unifying regulations based on key principles such as safety, performance, and transparency.

C. UAV MANAGEMENT

Dung et al. introduced regulations for drones and suggested drone following models to manage drones in urban environments [25]. The presence of multiple drones in the sky poses a higher risk of accidents, thereby endangering urban air transport infrastructure, such as buildings and public areas, as well as the safety of the environment [26]. Therefore, managing drones in urban areas has become crucial. The studies proposed a new approach to drone management called the drone-following model, which involves the one-by-one following of drone vehicles in urban air transport. This approach is based on defining drone acceleration, which depends on variations in velocities and gaps between the given drone and its front one. The numerical simulation results showed that maintaining a safe distance between drones prevented traffic flow accidents. However, to improve the proposed method, the equations of motion for drones need to be incorporated into these models, despite the fact that the numerically simulated results demonstrate the potential for enhancing powerful simulation technologies or a new prototype of controls.

TABLE 1. Summary of related works.

Category	Summary	Ref.
UAV Safety and Privacy	This section discusses the safety risks and privacy concerns associated with drone usage. It presents studies on safety and privacy regulations for drones in different regions, as well as schemes for tracking and identifying drones while preserving privacy.	[16] [17] [18]
Regulation and Constraint	This section focuses on drone regulations, compliance and the integration of drones into national airspace systems. It covers studies on user perspectives, public safety, data protection, and ethical considerations. Various research highlights the need for balanced regulations to ensure safety and privacy while reaping the benefits of drone technology.	[19] [20] [21] [22] [18] [23] [10] [24]
UAV Management	This section introduces the concept of drone management in urban environments. It proposes a drone-following model as an approach to manage multiple drones in urban air transport by maintaining safe distances between them. Numerical simulations suggest the potential for enhancing this method by incorporating drone motion equations.	[25] [26]

After reviewing the relevant literature, it can be inferred that most countries acknowledge the proliferation of UAV/drone usage and the potential risks they pose to humans, and as a result, many efforts have been made to address these concerns, although they have not been entirely successful.

To ensure safety, it is necessary to develop a safety system to apply specific regulations for particular areas, particularly in those that impact human activities.

III. IMPROVED PARTICLE SWARM OPTIMIZATION (IPSO)

A population based meta-heuristic particle swarm optimization algorithm has been widely applied to a variety of problems. The graphical representation of standard PSO algorithm is shown in Fig. 2. The standard PSO algorithm faces challenges such as getting stuck in local optima and premature convergence. These issues can limit the algorithm's ability to find the global optimum or hinder its exploration of the search space.

Local optima occur when particles converge towards a sub-optimal solution in their local neighborhood, preventing further exploration of potentially better solutions in other regions of the search space. This can happen if the algorithm lacks sufficient diversity or if particles are influenced too strongly by their immediate best-known positions. A premature convergence refers to the situation where the algorithm stops exploring the search space prematurely and settles on a sub-optimal solution. This can occur if the algorithm converges too quickly, before thoroughly exploring the entire search space. The premature convergence can be particularly challenging when dealing with complex or multi-modal optimization problems.

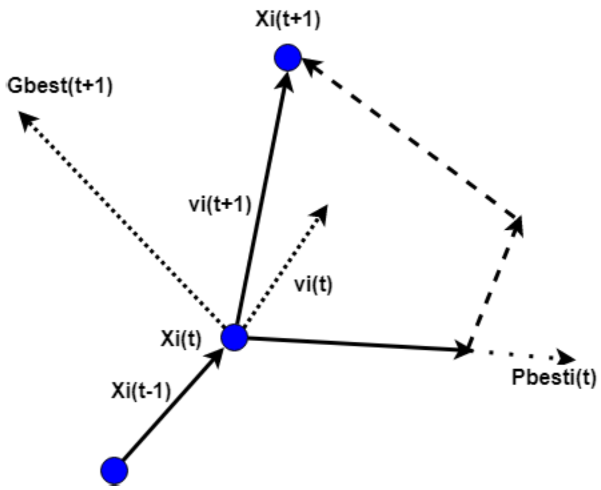

FIGURE 2. Graphical representation for standard PSO.

To cope with these challenges, The improved version of PSO, IPSO, is proposed. The improving includes provides better initialization of swarm particles, improved updating strategy, and replacement of inactive particles. A chaos-based initialization of particles using the logistic map is applied to improve diversity of solution space. The following logistic map initialization is utilized

$$X_{n+1} = \mu X_n(1 - X_n) \quad (1)$$

where X_n represents the n^{th} chaotic variable, μ is a bifurcation coefficient.

IPSO aims to achieve two main goals during the optimization process, namely convergence and searching, in order to find the optimal solution. Essentially, during the initial stage of iterations, the focus should be on searching or exploration to enhance diversity, while during the later stage, emphasis should be on convergence. To address issues such as premature convergence and insufficient exploration, an adaptive mutation technique has been developed. This involves updating the positions and velocities of particles mathematically at each iteration as follow:

$$v_{t+1} = \omega v_t + c_1 r_1(pBest_t - x_t) + c_2 r_2(gBest_t - x_t) \quad (2)$$

where ω is inertia weight and it is updated adaptively each iteration for achieving a balance between local and global search in optimization. To clarify, in optimization problems, maintaining a balance between exploration and exploitation is crucial, and this is where inertia weight adjustment plays a vital role. Exploration involves searching for new solutions, while exploitation focuses on refining existing solutions. Striking the right balance is important because excessive exploration can hinder convergence to the global optimum, while excessive exploitation can lead to being stuck in local optima. By adjusting the inertia weight, the algorithm can control the trade-off between exploration and exploitation. Initially, a higher inertia weight promotes exploration to prevent premature convergence, while gradually reducing the inertia weight shifts the focus towards exploitation to fine-tune solutions. Achieving the optimal balance ensures effective exploration of the search space while steadily converging towards the best solution, resulting in improved performance in optimization problems.

To achieve this, the concept of inertia weight is used to balance the exploration and exploitation phases of the search. In simple terms, a high value of ω promotes exploration of the search space, while a low value facilitates exploitation. To clarify this further, ω is adjusted linearly based on a certain formula as follow

$$\omega(t) = \omega_{min} + \frac{MaxIt - t}{MaxIt} * (\omega_{max} - \omega_{min}) \quad (3)$$

where $MaxIt$ is maximum simulation time and t is current simulation time, $\omega_{min}, \omega_{max}$ are minimum and maximum value of inertia, respectively.

The acceleration values c1 and c2 are used to determine the weight of the stochastic acceleration term in particles' velocity. When these values are multiplied by random vectors r1 and r2, they can have a controlled stochastic effect on the velocity. Furthermore, they represent the weight of information sharing among particles. For instance, if both c1 and c2 are set to zero, a particle relies solely on its own knowledge. However, if c1 is greater than c2, particles tend to move towards the local attractor, while if c2 is greater than c1, particles tend towards the global attractor. It is better if c1 and c2 are selected based on running experiments within the range of c_{min} to c_{max}. The aim is to choose values that achieve both exploration and exploitation. Finally, the position of particles is calculated using the following formula.

$$x(t + 1) = x(t) + \epsilon v(t + 1) \quad (4)$$

The value of ϵ determines the speed at which the particle moves. A high value of ϵ enables the system to quickly move towards the best-known regions but may make it difficult to perform fine-grained optimization. Conversely, a low value of ϵ fine-tunes the solution and accelerates convergence. To achieve a balance during the optimization process, the particle should initially explore the search space and make large jumps towards better regions. In later iterations, the speed of particles should be reduced to achieve faster convergence. Therefore, ϵ needs to be adapted dynamically with each iteration and can be written as follow:

$$\epsilon = \epsilon_{max} - \frac{(\epsilon_{max} - \epsilon_{min})t}{MaxIt} \quad (5)$$

where ϵ_{max}, ϵ_{min} are constant value and $\epsilon_{max} > \epsilon_{min}$, t is current simulation time and *MaxIt* is total simulation time.

IV. UAVS PATH PLANNING DESCRIPTION

In this system, we aim to provide a safety path for maximum UAVs capacity flying from source locations to their destinations safely. The mission environment may include obstacles such as mountains, buildings, radars, and other threats. Moreover, the UAVs formation includes many drones flying in the environment. Thus, to plan the path of UAVs formation, the terrain and formation constraints are taken into account such as obstacles in the terrain, and UAVs formation. The UAVs formation should be able to avoid colliding with these obstacles. To do so, objective function should include all these threats and obstacles in addition to regulation constraints and reflects the impact of them on performance.

The positions of UAVs formation can be represented as follow:

$$(p_1, v_1), (p_2, v_2), \ldots, (p_N, v_N) \tag{6}$$

To describe a three dimensional path planning problem, let N is the number of way points for each particle, then the i^{th} particle's position and velocity vector can be respectively written as in [27] as follow

$$p_i = p_i(x_1, y_1, z_1), p_i(x_2, y_2, z_2), \ldots, p_i(x_N, y_N, z_N) \tag{7}$$

$$v_i = v_i(x_1, y_1, z_1), v_i(x_2, y_2, z_2), \ldots, vi_{(x_N, y_N, z_N)} \tag{8}$$

A. IOD PATH REPRESENTATION

Optimization algorithms are utilized in path planning to determine a viable route for a drone to travel from a starting point to a destination point within a complex environment. The path should be suitable for use by the algorithm, and the flying space must be confined. In the context of 3D path planning, the boundary of the flying space can be described as in [27]

$$(x, y, z)|x_{min} \leq x \leq x_{max}, y_{min} \leq y \leq y_{max}, z_{min} \leq z \leq z_{max} \tag{9}$$

where $x_{min}, y_{min}, z_{min}$ are the lower bounds of the flying space and $x_{max}, y_{max}, z_{max}$ are the upper bounds of the flying space.

B. OBSTACLE MODEL

In this work, the space boundaries and locations of obstacles are assumed to be known in advance. We model the obstacle as a half sphere as in [27], as follow

$$O_k = (x_k, y_k, z_k, r_k) \tag{10}$$

where x_k, y_k, z_k are the three-dimensional coordinate of kth obstacle and r$_k$ is the corresponding radius of the obstacle.

$$x_k = r_k \cos(\theta)\sin(\phi) + x_{k0} \tag{11}$$

$$y_k = r_k \sin(\theta)\sin(\phi) + y_{k0} \tag{12}$$

$$z_k = r_k \cos(\phi) + z_{k0} \tag{13}$$

where x_{k0}, y_{k0}, z_{k0} is the center coordinate of kth obstacle, $\theta \in [0\ 2\pi]$, and $\phi \in [0\ \frac{\pi}{2}]$.

V. DESCRIPTION OF SYSTEM MODEL

The proposed approach aims to maximize the number of UAVs operated in a target region while adhering regulations. To do so, the following steps can be taken:

1) Determine regulation constraints: Determine the maximum speed at which the UAVs can safely operate while maintaining collision avoidance rules.
2) Establish collision avoidance rules: Establishing collision avoidance rules is essential to ensure that the UAVs do not collide during flight. This can be accomplished by maintaining the minimum safe distance between UAVs, as well as rules for avoiding obstacles in the airspace
3) Optimize flight paths to maximize the number of UAVs that can fly within the collision avoidance and speed constraints. This can be done using algorithms that consider the UAV's minimum safe distance, and other factors.
4) Monitor and adjust: Finally, monitor the UAVs during flight and adjust the flight paths as necessary to ensure UAVs safety within the collision avoidance and other constraints.

By following these steps, it is possible to maximize the number of UAVs flying under collision avoidance and UAV speed constraints. To accomplish this task, constraints are properly formulated and included in the problem.

A. DESIGN OF CONSTRAINTS

- Obstacles constraint: Let N_Obs is the number of obstacles and NFZs, and Nd is a number of UAVs. The obstacle constraint, $Obc(i, j)$, i=1,2,.., Nd, and j=1, 2,..., N_Obs, can be obtained as follow

$$Obc(i, j) = \sqrt{(Ux_i - Ox_j)^2 + (Uy_i - Oy_j)^2 + (Uz_i - Oz_j)^2} \tag{14}$$

If any point of UAV's path goes through obstacles, the path is penalized by a high value to discard it. Thus, the cost of collision with obstacle can be formulated as follow

$$J_1 = \begin{cases} inf, & \text{if } Obc(i, j) < R\_\text{obs}_j \\ 0, & \text{Otherwise} \end{cases}$$

- UAV member constraint: This constraint is to avoid collisions among UAVs in the flying space. The distance between UAVs is determined as follow

$$Uc(i, j) = \sqrt{(Ux_i - Ux_j)^2 + (Uy_i - Uy_j)^2 + (Uz_i - Uz_j)^2} \tag{15}$$

This constraint keeps tracking the distance between UAVs. If the distance between any two UAVs is smaller than a safety distance (SD), the paths are discarded. For doing so, the cost of collision with other members can be formulated as follow

$$J_2 = \begin{cases} inf, & \text{if } Uc(i,j) < \text{SD} \\ 0, & \text{Otherwise} \end{cases}$$

- Altitude constraint: The UAVs altitude constraint should not exceed 120 m. So, the constraint can be written as

$$J_3 = \begin{cases} inf, & \text{if UAV\_altitude} > 120 \text{ m} \\ 0, & \text{Otherwise} \end{cases}$$

- Speed constraint: The UAV's maximum speed constraint should not exceed 44 mps. So, the constraint can be written as

$$J_4 = \begin{cases} inf, & \text{if UAV\_speed} > 44 \text{ mps} \\ 0, & \text{Otherwise} \end{cases}$$

B. DESIGN OF LOCAL OBJECTIVE FUNCTION

The objective function is a mathematical concept that determines how various variables contribute to a specific value, and the optimization algorithm either maximizes or minimizes this value. In this subsection, we design the local objective function that is applied in IPSO to obtain the paths of UAVs.

One of the most important objective in UAV path planning is the energy consumption, and the path with minimum energy required is desirable. In this work, we apply the energy model used in [28] to calculate the energy for path. Therefore, the objective function can be written as follow

$$Obj\_Func = f_{Energy} + J_1 + J_2 + J_3 + J_4 \tag{16}$$

where f_{Energy} is a function of energy path, and J_1, J_2, J_3, and J_4 are violation costs of obstacle collision, member collision, altitude, and speed violation. The aim is to minimize these quantities.

C. PROBLEM FORMULATION

The problem of maximizing the number of UAVs flying under regulation, UAVs, and terrain constraints can be formulated as a maximization optimization problem. The objective is to maximize the number of UAVs that can fly in a given airspace while adhering to regulatory constraints, and collision avoidance rules. The variables in this problem are the number of UAVs and their corresponding flight paths. The following constraints are considered in this problem: In this study, it is important to emphasize that the terms ''UAVs capacity'' and ''region capacity'' are used interchangeably.

Collision avoidance constraint: this constraint dictates the minimum safe distance between UAVs, as well as constraint to avoid obstacles in the airspace and environment as explained above. The following assumptions can be made in formulating this problem:

- Each UAV is of the same type and has similar flight characteristics.
- The weather-related hazards of airspace are discarded.

With these components defined, we can formulate the problem as a maximization optimization problem, with the objective of maximizing the number of UAVs that can fly in a given airspace subject to the regulatory constraints, collision avoidance, and UAV speed constraints. The problem is solved using approximation optimization techniques, IPSO. The solution will provide the optimal number of UAVs and their corresponding flight paths that achieves the objective while adhering to the regulation constraints.

Let R is a region of interest that involves N_r forbidden regions or NFZs, in which UAVs are not allowed to fly through them, and M_O obstacles randomly distributed throughout the region. So, $N\_Obs = M_O + N_r$.

We assume that UAVs are tasked to fly from starting positions (SPs) to target positions (TPs). UAVs are not allowed to fly above 120 m altitude, and greater than 44 m/s speed. The aim is to find the maximum available UAVs in this region without colliding with obstacles or with other UAVs. For simplicity, the shape of a region is assumed to be a square or rectangular.

Therefore, the problem can be formulated as follows: The global objective function can be written as

$$Max\ J = UAV\ s\ Capacity \tag{17}$$

Subject to the following constraints:

- The distance between any UAV_i and $obstacle_j$, Obc(i,j) $> R\_obs_j$. $i \in [1, N_d]$, and $j \in [1, N\_Obs]$.
- A safety distance should be maintained between UAVs, Uc(i,j) $> SD$, $i, j \in [1, N_d]$.
- Maximum UAV speed $<$ 44 mps.
- Maximum flying altitude $\leq$ 120 m.

D. OPTIMIZATION ALGORITHM FOR THE SYSTEM MODEL

This subsection describes in details the proposed approach, and the IPSO for UAVs path planning algorithm.

The proposed approach illustrated in algorithm 1 and 2, and flowchart, Fig. 3, provides a valuable tool for determining the maximum capacity of UAVs that can operate safely within a given area while fulfilling with regulation and terrain constraints. As depicted in flow chart of the developed algorithm, Figure 3, it uses an iterative approach, starting with a certain number of UAVs and incrementally increasing the number of UAVs until a collision is detected.T he maximum capacity of UAVs is determined by considering the number of UAVs present before a collision occurs.

To optimize the path of the UAVs, the algorithm utilizes the improved particle swarm optimization algorithm, a variant of the particle swarm optimization algorithm. An IPSO introduces new particle update rules to improve the performance of PSO. This optimization technique ensures that the UAVs plan their paths while maintaining a safe distance between them and complying with the regulation and terrain constraints.

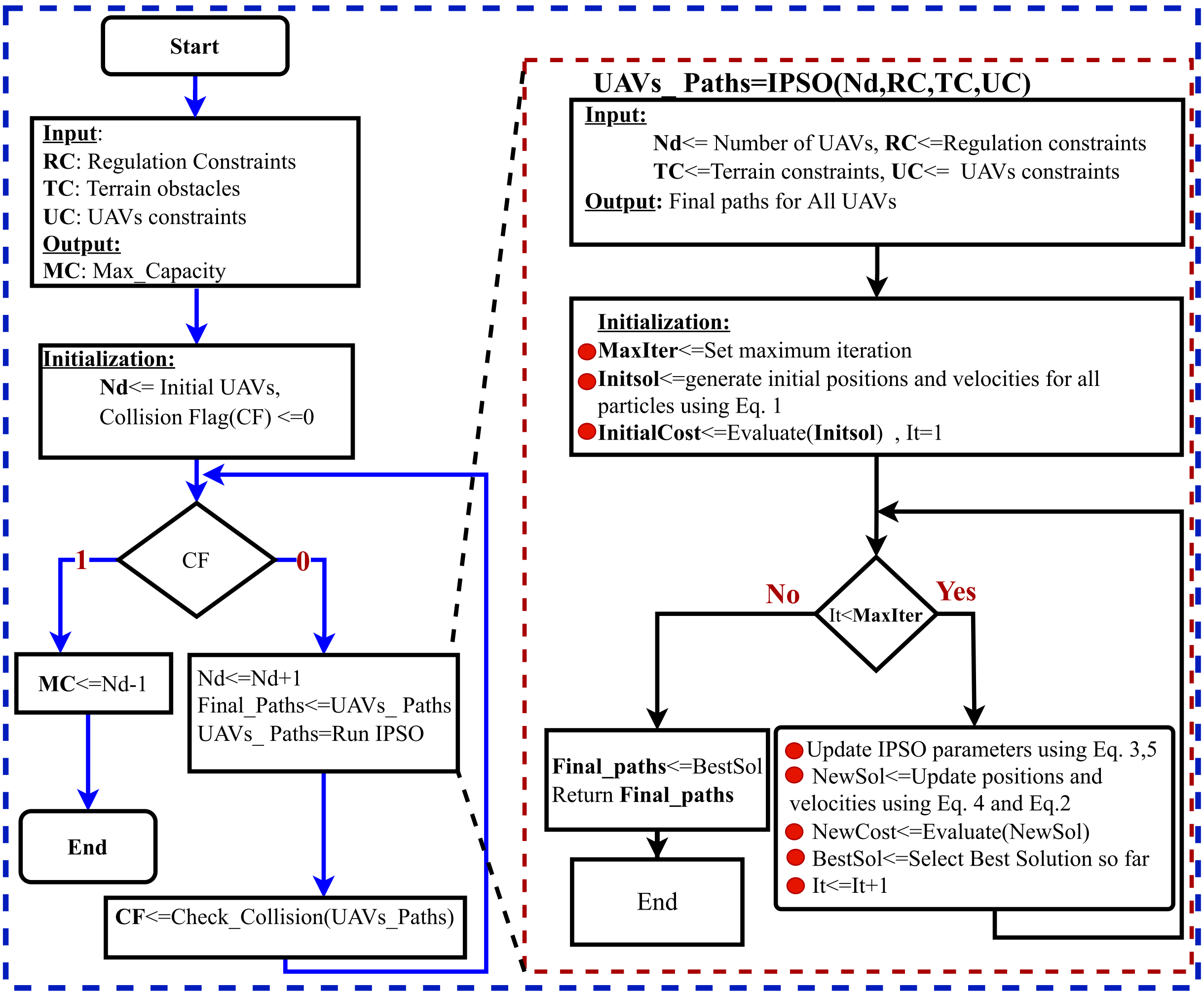

FIGURE 3. Flowchart of the proposed optimization approach.

Algorithm 2 is an enhanced version of PSO that comprises several parts. The algorithm begins with the initialization stage, which is responsible for initializing all variables, and creating the initial solution, as well as determines the position and velocity of each particle. The path planning generator takes into account various parameters and environmental constraints and produces viable paths for all drones, along with the corresponding energy cost.

To make things clearer, we'll provide a more detailed explanation of the algorithm. The algorithm receives regulation, region, and UAVs constraints, and returns the UAVs paths. To begin, the algorithm sets the maximum number of iterations and generates an initial population of particles. The particles' positions and velocities are generated using chaotic initialization within the search space using an equation 1. The cost of the initial population is then calculated by passing each particle's position to a cost function that evaluates the energy value of the corresponding solution. After initialization phase, the algorithm executes a loop that continues until the maximum number of iterations have been reached. In each iteration, the position and velocity of each particle are evolved with iteration. This is done by updating the positions and velocities of the particles, evaluating the cost of the new population, i.e., energy consumption, and tracking the best solution found so far. The algorithm uses three key parameters, the inertia weight, mutation, and the acceleration coefficients, to control the particles' movements.

The inertia weight determines how much of the particle's previous velocity is retained when calculating the new velocity, while the acceleration coefficients determine the impact of the particle's personal best and the swarm's best solution on the particle's movement. The IPSO parameters are updated using an equation 3 and 5 that depends on the current iteration number and the maximum number of iterations to enable adaptive mutation of the generated solution. The algorithm updates the velocity and position of each particle using the equation 2, and equation 4, respectively, that considers the current position, velocity, personal best, and global best solutions.

Algorithm 1 Maximum UAVs Capacity Under Regulation Constraints

Input:
RC← Regulation Constrains
TC← Terrain Constraints
UC← UAVs Members' Constraints
Output:
MC ← Maximum UAVs Capacity
Initialization:
N_d ←Initial number of UAVs
Collision-Flag(CF)←0
Formulation←Formulate the problem as a maximization optimization problem
while CF==0 **do**
    $N_d \leftarrow N_d + 1$
    UAVs-Paths←IPSO(N_d,RC,TC,UC,SD) %[algorithm 2]
    CF←Check-Collision(UAVs-Paths)
end while
MC← N_d-1
Return Maximum allowable UAVs capacity (MC)

Algorithm 2 Improved PSO Algorithm for UAVs Path Planning

Input:
Nd← number of UAVs
RC← regulation constraints
TC← terrain constraints
UC← UAV self constraints
Output: Optimal paths of all UAVs
INITIALIZATION:
MaxIter← maximum iteration
InitSol← initialize positions and velocities with logistic map by Eq1
Initial_EnergyCost← Evaluate(InitSol)
Iter=1
while Iter<MaxIter **do**
    Update IPSO parameters by Eq3 and Eq5
    Update the velocities of particles for all populations using Eq2
    Update the positions of particles for all populations using Eq4
    New_EnergyCost← Evaluate the energy cost of generated particles
    BestSol← Select Best Solution so far
    Replace inactive particles
    Increment Iter
end while
Return Optimal paths for all UAVs

The new position and velocity are calculated by considering the particle's distance to its personal best solution and its distance to the global best solution. More importantly, the algorithm keeps track of particles that can't participate in solution improvement, and replaces inactive particles by fresh one to prevent sticking in a local optimum. The cost of the new population is evaluated by passing each particle's new position to the cost function. The best solution found so far is determined by selecting the path with the lowest energy consumption among all particles in the population, which is known as the global best solution. The iteration counter is incremented by 1, and the while loop ends once the maximum number of iterations is reached. The algorithm returns the best paths for all UAVs.

To detect collisions between the UAVs, the algorithm 1 uses a *Check-Collision* function that checks if the constraint safety distance between any two UAVs is maintained. Moreover, the *Check-Collision* function also checks for collision with terrain obstacles. If a collision is detected, the algorithm stops and returns the maximum capacity of UAVs. The Collision-Flag (CF) is raised to indicate the occurrence of a collision.

It is important to note that the algorithm assumes that the regulation and terrain constraints are fixed and do not change during UAVs' operations. Additionally, the algorithm assumes that the UAVs have the same characteristics, such as flight speed and range.

TABLE 2. Parameters setting.

Parameter	Value	Parameter	Value		
Optimization approach	IPSO		Scenario 1	Scenario 2	Scenario 3
Population size	200	boundary	1 Km x 1Km	2Km x 2Km	500 m x 500 m
Max Iteration	300	Obstacles	6	18	5
Altitude	60,100,120 m	NFZs	3	5	3
Obstacle and NFZs size	Ranging from 50 m to 104.12 m				Ranging from 5 m to 10 m

VI. SIMULATION RESULTS AND DISCUSSION

Simulation is an effective way to verify results. It is noteworthy to describe in detail how the simulation results are recorded in the figures. This section illustrates the simulation of the proposed method for fixed and variable altitudes.

The matlab environment is used for simulation on PC with an Intel Core i7 CPU, 1.90GHz (8 CPUs), and 16 GB Ram.

A. PARAMETERS SETTING

In this study, we consider three scenarios; in scenario1: a region size is 1000 m × 1000 m. The number of obstacles and NFZs are set to 6 and 3, respectively, which are randomly distributed throughout the region. In scenario2, a region size is 2000 m × 2000 m. Eighteen obstacles and five NFZs are randomly distributed throughout the region. In both scenarios, drones are flying at fixed altitude of 60 m, 100 m, and 120 m, a safety distance between UAVs is set to 10 m, and sizes of obstacles and NFZs are ranging from 50 m to 104.12 m.

In the third scenario, a region size is 500 m × 500 m. Number of obstacles and NFZs, are 5 and 3, respectively, that are randomly distributed throughout the region. The sizes of obstacles and NFZs are ranging from 15 m to 70 m. The UAVs

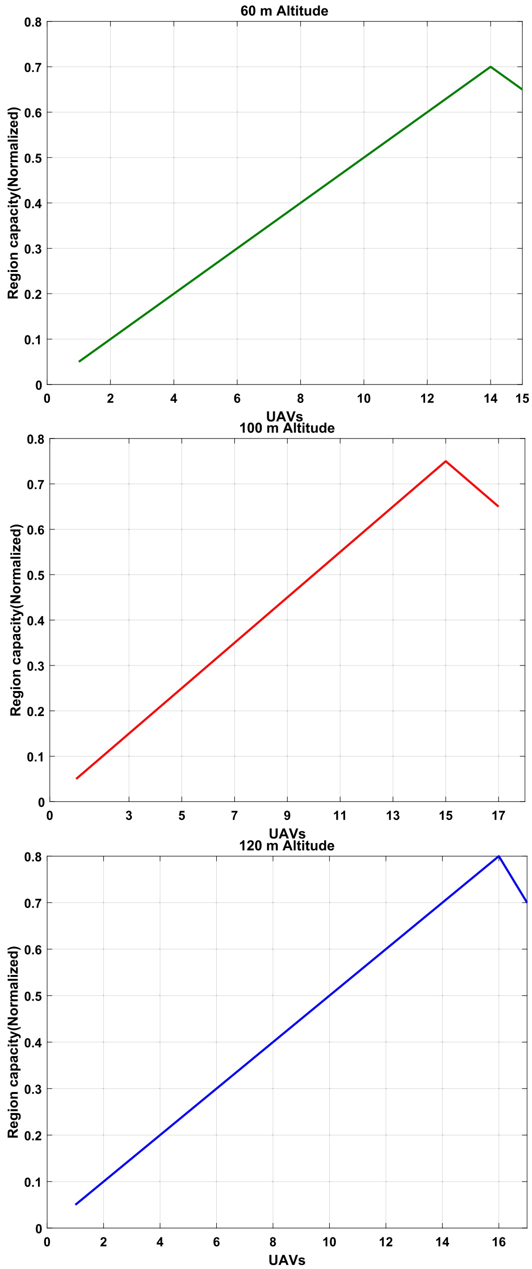

FIGURE 4. **Scenario 1: Normalized region capacity with respect to UAVs.**

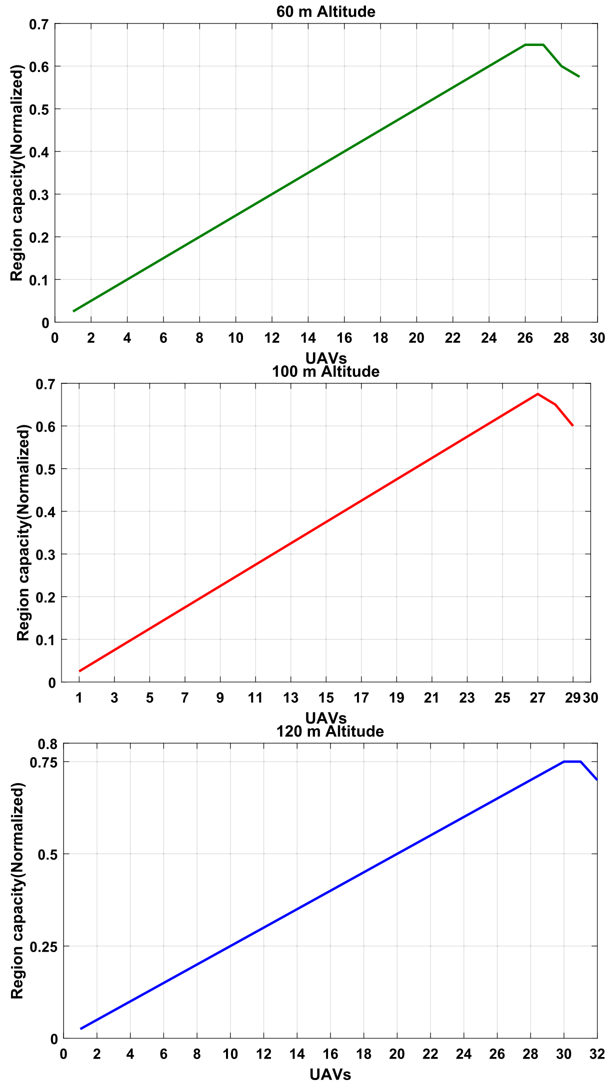

FIGURE 5. **Scenario 2: Normalized region capacity with respect to UAVs.**

are flying at 50 m, 60 m, 80 m, and 100 m altitudes. we repeat the simulation 30 times, and the results are the average of 30 runs.

In all scenarios, the population size is set to 200 and the maximum number of iterations is set to 300. The parameters setting are presented in Table 2. The performance (region capacity) is defined by the maximum number of UAVs arrived to their destinations successfully.

B. RESULTS AND DISCUSSION

In this part, we will study the effectiveness of the proposed optimization approach according to maximum region capacity.

1) IMPACT OF REGION OBSTACLES AND NFZS ON REGION CAPACITY

In this subsection, we study the impact of obstacles and NFZs on the overall capacity of a given region. In our study, UAVs are allowed to fly at different fixed altitudes, while the dimensions of x and y can vary. By analyzing two specific scenarios, we aim to determine the maximum number of UAVs that can safely operate within this environment.

In the first scenario, we observe the behavior of UAVs within the region and the number of UAVs progressively increases till reach the maximum region capacity in which a collision occurs, indicating that any further increase in the number of UAVs would compromise safety. We present the results of this scenario in Fig. 4. Similarly, in the second scenario, we investigate the maximum number of UAVs that can operate safely in the presence of obstacles and NFZs. The results of this analysis are depicted in Fig. 5. To provide a visual representation of the UAVs' trajectories, we include

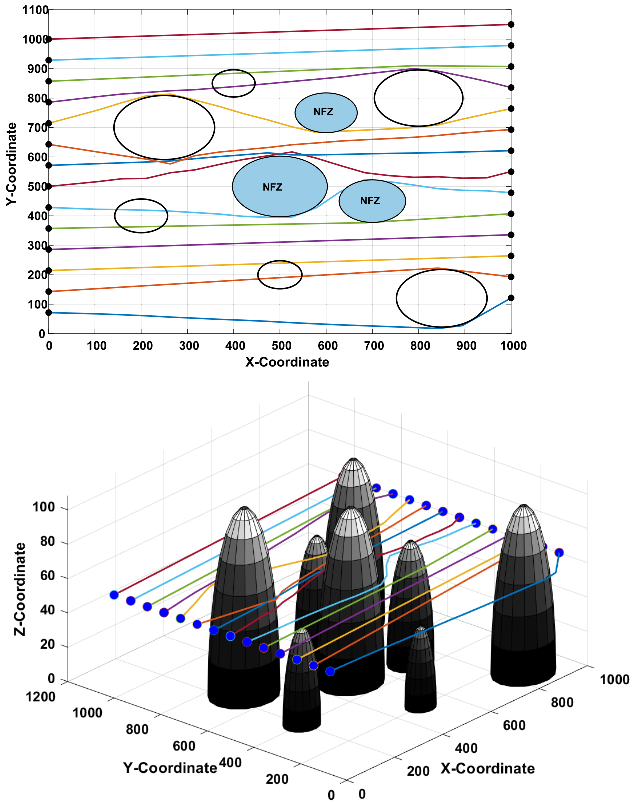

FIGURE 6. Two and three dimensional view for UAVs paths by IPSO.

both two-dimensional and three-dimensional views in Fig. 6. These figures clearly demonstrate the feasible paths taken by all UAVs, without any conflicts with terrain obstacles.

By examining these figures and analyzing the impact of obstacles and NFZs, we can gain valuable insights into the region's capacity for UAV operations. This information is essential for ensuring the safe and efficient utilization of UAVs within the given environment.

2) IMPACT OF OBSTACLES AND NFZS ON REGION CAPACITY

In this particular section, we delve into the impact that obstacles and NFZs have on the overall capacity of the region, focusing specifically on scenario 2. Within NFZs, UAVs are strictly prohibited from flying above them, even at high altitudes. Conversely, when encountering obstacles, UAVs have the option to circumvent them by flying over them. Our objective is to examine how the presence of NFZs affects the region's capacity.

To conduct this study, we gradually increase the number of obstacles and NFZs in the scenario. Specifically, we consider different quantities, starting from zero and incrementing by intervals of 5 (i.e., 0, 5, 11, 17, 23). The resulting findings are presented in Fig. 7. The figure clearly demonstrates that as the number of obstacles and NFZs increases, the region's capacity decreases. This showcases the tangible impact that obstacles and NFZs have on the overall capacity of the region.

By observing this trend, we can gain valuable insights into the limitations imposed by obstacles and NFZs, which are crucial factors to consider when planning UAV operations in the area. By thoroughly analyzing these results, we can make informed decisions and develop strategies to overcome the challenges posed by obstacles and NFZs, ultimately enhancing the region's capacity for UAV operations while ensuring compliance with safety regulations and restrictions.

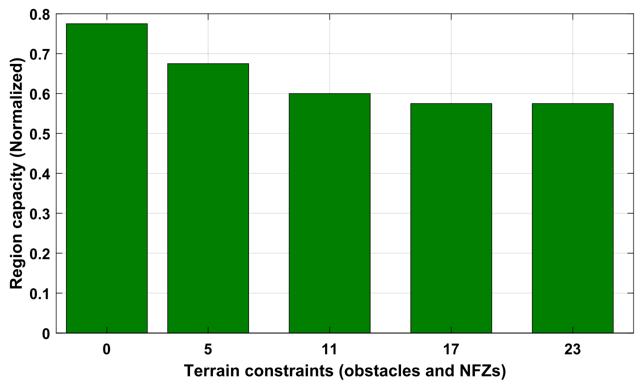

FIGURE 7. Normalized region capacity for different number of obstacles and NFZs exist.

3) EFFECT OF UAV ALTITUDE ON REGION CAPACITY

In this subsection, we study the impact of flying altitude on a region capacity. We consider two scenarios, fixed level and multi-level altitudes. Results are depicted in Fig. 8.

The altitude of a UAV is a key factor that affects the region capacity and collision risk. As the UAV flies at a higher altitude, it creates a larger buffer zone between the drone and the ground obstacles, which can reduce the risk of collision. This is because the UAV has a wider field of view that allows it to detect obstacles from a greater distance, giving it more time to adjust its flight path and avoid collisions. Also, high altitude allows UAV to fly above obstacles and thus; reduces the impact of obstacles. As a result, when the flying altitude increases, the number of drones that can operate also increases due to a reduction in the impact of terrain obstacles. This advantage tends to grow higher in multi-level altitudes. This is because in multi-level altitudes, the UAVs' member constraint can be addressed by flying in different levels, and thus avoid collision with other UAVs. It can be observed from Fig. 8 that flying at an altitude above 80 m does not increase the maximum capacity. This is because the maximum height of obstacles is limited to 70 m, and therefore, there is no effect of obstacles on the maximum capacity. Nevertheless, flying at higher altitudes also increases the possibility of collision with other aircraft, including commercial planes and other drones. The airspace at higher altitudes is more congested, thus leading to a greater potential for conflicts between different flying objects. Therefore, while flying at a higher altitude can reduce the risk of collision with ground obstacles, it may also increase the risk of collision with other flying objects.

The proposed approach address this issue by restricting the flying altitude to flying constraint, which is less that 120 m altitude. Additionally, the proposed approach considers the collision with other drones in the formation by maintaining a sufficient safety distance between drones to avoid collision.

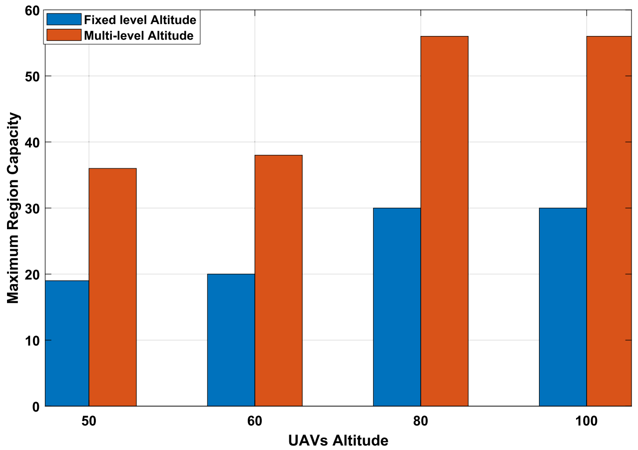

FIGURE 8. Region capacity with respect to different altitudes for fixed and multi-level altitudes.

VII. CONCLUSION

In this work, we proposed a safety system for maximizing the capacity of UAVs while adhering to regulation constraints. The proposed system considered various factors such as NFZs, altitude limits, and terrain obstacles to optimize the trajectory of the UAVs. The algorithm provided a reliable method for determining the maximum capacity of UAVs that could operate safely within a given area while adhering with regulation and terrain constraints. The proposed safety system was evaluated through simulations, and the results demonstrated its effectiveness in maximizing the capacity of UAVs while adhering to regulation constraints. The results of our simulations demonstrated that the proposed system successfully increased UAVs capacity to the maximum possible while maintaining safety and adhering to regulatory constraints. This has significant implications for real-world UAV operations, particularly in complex and regulated air spaces. By employing our system, it can optimize operations, improve efficiency, and maximize the number of UAVs that can operate safely within a given area.

For future work and improvements to our system, one potential avenue for further investigation is the integration of real-time data and dynamic airspace constraints into the optimization process. This would allow the system to adapt to changing conditions and optimize UAV trajectories in real-time, enhancing operational efficiency and safety.

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