applied sciences

MDPI

Article

Adaptive Metaheuristic-Based Methods for Autonomous Robot Path Planning: Sustainable Agricultural Applications

Farzad Kiani [1,*,†], Amir Seyyedabbasi [1,2], Sajjad Nematzadeh [3], Fuat Candan [4], Taner Çevik [3], Fateme Aysin Anka [5,‡], Giovanni Randazzo [6], Stefania Lanza [7] and Anselme Muzirafuti [6,*]

[1] Software Engineering Department, Faculty of Engineering and Natural Science, Istinye University, Istanbul 34396, Turkey; amir.seyyedabbasi@gmail.com
[2] Computer Engineering Department, Faculty of Engineering and Architecture, Beykent University, Istanbul 34398, Turkey
[3] Computer Engineering Department, Faculty of Engineering and Architecture, Nisantasi University, Istanbul 34398, Turkey; nematzadeh.sajjad@gmail.com (S.N.); taner.cevik@nisantasi.edu.tr (T.Ç.)
[4] Computer Engineering Department, Faculty of Engineering and Natural Science, Istanbul Sabahattin Zaim University, Istanbul 34303, Turkey; fuat.candan@std.izu.edu.tr
[5] Political Science and Public Administration Department, Faculty of Economics, Administrative and Social Sciences, Istinye University, Istanbul 34396, Turkey; fatemeh.dehghan@istinye.edu.tr
[6] Dipartimento di Scienze Matematiche e Informatiche, Scienze Fisiche e Scienze della Terra, Università degli Studi di Messina, Via F. Stagno d'Alcontres, 31-98166 Messina, Italy; giovanni.randazzo@unime.it
[7] GeoloGIS s.r.l., Dipartimento di Scienze Matematiche e Informatiche, Scienze Fisiche e Scienze della Terra, Università degli di Messina, Via F. Stagno d'Alcontres, 31-98166 Messina, Italy; stefania.lanza@unime.it
* Correspondence: farzad.kiyani@gmail.com (F.K.); anselme.muzirafuti@unime.it (A.M.); Tel.: +90-850-283-6000 (F.K.)
† Other publish name is Ferzat Anka.
‡ Other publish name is Fatemeh Dehghan Khangahi.

check for updates

Citation: Kiani, F.; Seyyedabbasi, A.; Nematzadeh, S.; Candan, F.; Çevik, T.; Anka, F.A.; Randazzo, G.; Lanza, S.; Muzirafuti, A. Adaptive Metaheuristic-Based Methods for Autonomous Robot Path Planning: Sustainable Agricultural Applications. *Appl. Sci.* **2022**, *12*, 943. https://doi.org/10.3390/app12030943

Academic Editor: José Miguel Molina Martínez

Received: 28 December 2021
Accepted: 10 January 2022
Published: 18 January 2022

Abstract: The increasing need for food in recent years means that environmental protection and sustainable agriculture are necessary. For this, smart agricultural systems and autonomous robots have become widespread. One of the most significant and persistent problems related to robots is 3D path planning, which is an NP-hard problem, for mobile robots. In this paper, efficient methods are proposed by two metaheuristic algorithms (Incremental Gray Wolf Optimization (I-GWO) and Expanded Gray Wolf Optimization (Ex-GWO)). The proposed methods try to find collision-free optimal paths between two points for robots without human intervention in an acceptable time with the lowest process costs and efficient use of resources in large-scale and crowded farmlands. Thanks to the methods proposed in this study, various tasks such as tracking crops can be performed efficiently by autonomous robots. The simulations are carried out using three methods, and the obtained results are compared with each other and analyzed. The relevant results show that in the proposed methods, the mobile robots avoid the obstacles successfully and obtain the optimal path cost from source to destination. According to the simulation results, the proposed method based on the Ex-GWO algorithm has a better success rate of 55.56% in optimal path cost.

Keywords: autonomous robots; remote sensing; smart agriculture; climate change; environmental protection; drone; photogrammetry; path planning; internet of things; environmental monitoring

1. Introduction

In recent years, environmental protection and sustainability have become fundamental needs. Environmental sustainability is the conservation of natural resources and meeting the needs of future generations to avoid potential hazards, and for this purpose, it is vital to interact with the planet responsibly. In this situation, it is necessary to provide future generations with a lifestyle at least an equal in quality to the current generations, and in this direction, it is necessary to use existing natural resources efficiently [1]. In recent times, one of the most popular areas of sustainability is agriculture. In the last few years, researchers have made traditional agriculture more efficient and functional with new technologies, concepts, and methods within the scope of smart agriculture. In this context, sustainable agriculture can be achieved, and resources such as human and natural resources will be used more efficiently. On the other hand, with the prediction that the world population will reach 9 billion people by 2050, agricultural products should be increased by 70% [2]. Currently, the food industry is responsible for 30% of the world's energy consumed and 22% of greenhouse gas emissions. In addition, if a product variety is not suitable for certain regional conditions and the planning in planting and harvesting is wrong, it causes the overconsumption of resources, crop culling, and consequent food shortages. These problems may even cause forced migration in some regions [3]. Therefore, the agricultural sector has to address serious issues such as climate change issues, limited arable land, and increasing demand for freshwater. In this regard, it is essential that the development policies of states for agriculture are in a sustainable framework [4].

The role of smart systems in sustainable agriculture is increasing day by day. In this direction, many technological methods are used and recommended. One of them is to use autonomous robots' technology, but in an environment with many autonomous robots and obstacles, one of the most critical tasks is to transfer these robots safely between two points without them colliding with each other or with obstacles. For an autonomous robot, the problem of searching for a safe path from a source to a destination is called path planning [5,6]. This issue can be addressed using various new technologies (e.g., Wireless Sensor Networks (WSNs) and Internet of Things (IoT)) that have a wide range of applications [7–9] since they can be designed with heterogeneous or homogeneous devices in distributed, central, or Peer-to-Peer (P2P) architectures. One of the application areas of these technologies which has become popular in recent years is agriculture [10–13]. This field has a wide range of smart applications and systems from the cultivation of agricultural products to their logistics [14–17]. Although there are many agricultural studies in the literature, the design of smart and autonomous devices and applications that use effective and efficient resources have not been developed. One of them is the proposal of efficient 3D path planning algorithms for mobile devices used in large-scale farmlands, which has many obstacles.

It is important to consider the environment in three dimensions in order for it to be applicable to real-world applications and projects in complex environments. Furthermore, when it comes to mobile robots, three-dimensional movements and areas seem more acceptable. In real application areas, considering the resources of mobile robots, such as energy, finding the optimal path is important. Optimal path planning means that the shortest path length, where the selected path is as far as possible from obstacles, must be smooth without sharp turns and must consider motion constraints. Finding an optimal 3D path planning is a Non-deterministic Polynomial-time (NP-hard) problem [5,6]. This makes metaheuristic algorithms a good choice for designing a solution to such a problem. Considering that large-scale environments in 3D environments increase the applicability of this study in real applications, as such, one of the fundamental problems related to robots from past to present is 3D path planning for aerial robots. This problem can become even more complex in large-scale agricultural areas with many obstacles.

In this study, we focused on Gray Wolf Optimizer (GWO)-based algorithms to solve the mentioned problem. In general, GWO-based algorithms have a balanced behavior transition between discovery and use phases because they use the hierarchical group working mechanism of wolves, and they also use a minimum number of control mathematical parameters. In this way, the chance of finding the optimal solution in a short time is high; in addition, the use of resources is also efficient. On the other hand, a GWO-based method was proposed in [18] for solving the mentioned problem, and they proved it was better than other metaheuristic-based algorithms. In this study, two methods, inspired by Incremental Gray Wolf Optimization (I-GWO) [19] and Expanded Gray Wolf Optimization (Ex-GWO) [19], are proposed to address the above issue. The classical GWO algorithm can behave more stably in normal situations (for a somewhat standard environment without many obstacles). The Ex-GWO-based path planning method may be performed more successfully in larger and more crowded environments with larger populations and iterations, and the I-GWO-based path planning method may give good results in medium and smaller, less populated environments. However, the I-GWO is faster than other algorithms.

These methods can be applied in different and diverse agricultural application areas and thus can be useful work for farming and smart agriculture. This paper presents optimized, reliable, and shortest pathfinding mechanisms for smart agricultural robots (e.g., autonomous tractors and agricultural drones) that track crops on large-scale farmlands without the need for the intervention of any human using distributed IoT [20] and WSN technologies. Thanks to the algorithms proposed in this study, efficient resource consumption and product growth rate can be achieved with low risk and cost. On the other hand, avoiding obstacles in the path planning of agricultural areas is more complex than in other path planning areas because of a dense population of objects that can serve as obstacles such as trees, plants, and buildings. As mentioned above, the most critical problem these mobile robots face is the efficient use of resources such as energy, so this issue is given importance in this paper. In other words, the management of resources with minimal loss is the aim of the paper. In addition, a smooth and efficient pathfinding mechanism is very important for robots; because of this, the system must showcase a sustainable performance. Therefore, the method used with the mobile robots must deliver them to the destination point using the best path. To achieve all these purposes, two different algorithms based on metaheuristic algorithms are presented for each autonomous mobile robot. Indeed, the proposed methods find collision-free optimal paths in an acceptable time with the lowest process costs in different environments containing various obstacles. In this study, it is assumed that there are many obstacles in agricultural land in order to ensure that environmental conditions are realistic. Therefore, the proposed algorithms are simulated and evaluated in a similar environment. The mobile robots in this farmland try to find the optimal paths while bypassing possible obstacles in the farmland with our proposed methods. In addition, in a developed application by the authors for farmers, these employed robots can be monitored and controlled.

In Section 2 of this paper, the literature studies are presented. The proposed algorithms and their related applications are explained in Section 3. In Section 4, the simulation results and performances of each method are evaluated. The last section of the paper includes the conclusions and possible further studies.

2. Literature Review

2.1. Unmanned Aerial Robots' Applications in Agriculture

IoT and similar technologies such as WSN, which have become popular in recent years, are used to meet the needs in the agriculture fields. Along with the IoT, the widespread use of autonomous robots such as Unmanned Aerial Robots (UAVs) increases productivity in agriculture. In recent years, studies related to this subject have gained acceleration [21–24]. In [25], the authors used UAVs to detect possible drainage pipes. Often, farmers need to repair or construct drain lines to efficiently remove water from soil. Therefore, in this study, they wanted to increase resource consumption and productivity in agriculture by focusing on this issue. In [26], the combined application of UAV and Unmanned Ground Robot (UGV) was proposed to monitor and manage crops. The authors proposed a system that can periodically monitor the condition of crops, capture multiple images of them, and determine the state of the crops. In addition to many UAV-based studies and products, recently, the concepts of IoT and autonomous robots have begun to be presented together. In this way, the data detected by the UAVs or each autonomous robot reach the place where they need to be sent instantly, the necessary actions can be taken on this data, and it can quickly provide a decision mechanism to the farmer or other technological devices. For example, in [27], the authors presented a farm monitoring system via UAV, IoT, and Long-Range Wide Area Network (LoRAWAN) technologies for efficient resource management and data delivery. In this regard, they monitored water quality. In [28], the authors proposed a new model to minimize the post-disaster inspection cost to serve a disaster-affected area. In this study, battery charging costs, service costs, drone hovering, turning, acceleration, cruise, and deceleration costs were considered. In this regard, the authors used two heuristics *(not meta-heuristics)* algorithms, but it was not possible to avoid the fundamental problems of heuristics [19]. In [29], the study aimed to deliver to a number of customers by UAVs, namely drones. Here, it focused on three issues. One was the launch points of the drones, the second was the launch points of the customers, and the third was the distance between the customer and the drone. The proposed method goal was to minimize the total operational cost, including an explicit calculation of the energy consumption of the drone as a function of the drone speed.

The most common role of drones in agriculture is to assess and monitor crops. For this, remote sensing is carried out, but this task is not enough when agricultural applications become more widespread. For this, autonomous mobile robots such as drones and other UAVs with technologically different features are designed for various agricultural purposes. In [30], the authors used satellite images to crop mapping. They used the remote sensing feature and utilized advantages of combined radar data and optical images to identify the type of crops. The authors claim that this combination provides an increased chance of examining details and provides more reliable information compared to a single-sensor classification method. We can generally categorize UAV/drone-based agricultural applications into three categories: Monitoring Applications, (b) Spraying Applications, and (c) Multi-robots Applications. In the first category, crops are tracked, and certain appropriate information and vegetation indices are extracted. For this, it is necessary to provide the imaging data that are processed later. Thus, we can identify problem areas in the crop that suffer from various diseases and pests. The data received by UAVs sensors can be characterized based on their spectral, spatial, and temporal properties. The selection of suitable sensors and data depends on the nature of their applications. There are many studies in the literature related to this [31–33]. Most studies in the second category have focused on applications that can spray pesticides and fertilizers in appropriate and correct amounts. Most of the papers reviewed install a spray device and take into account various conditions that can affect this process, such as weather [34–36]. We should not forget that these agricultural chemical products can cause various problems such as environmental disasters and human diseases such as cancer. Currently, most of the existing studies in the literature generally focus on a single autonomous, mobile robot performing a monitoring operation. For example, in some cases such as large crops, a single mobile device (e.g., UAV) cannot complete the monitoring process as it is characterized by limited power sources (limited battery). On the contrary, a multi-robot application can overcome this difficulty by dividing the area into multiple sub-areas corresponding to the number of UAVs/drones [37–39]. In addition, different purposes and applications are carried out on a single drone. However, the need for more than one mobile robot to work is increasing day by day. In particular, parallel processing is very important in terms of performance and process speed. In this regard, one of the most important issues is that these autonomous mobile robots can work together as soon as possible and use fewer resources without colliding with each other. The situation becomes even more difficult, especially in large-scale agricultural land, which consists of various barriers. Thus, the problem of path planning seems to be quite important, and an efficient mechanism can be used in many various agricultural applications; it can also be coded and embedded with different hardware devices. Therefore, in the next subsection, the topic of three-dimensional path planning in the literature is discussed.

2.2. Path Planning in Agricultural Applications

It is very important that autonomous robots used in smart agriculture perform their duties efficiently and that resources are used efficiently. In this regard, a vital issue is that these robots do their tasks with the most optimum mechanism. Therefore, it is necessary to focus on the NP-hard type of 3D path planning problem. A general classification of 3D path planning consists of four types, as shown in Figure 1. These types are sampling-based algorithms [40], node-based algorithms [41], mathematical-based algorithms [42], and nature-based algorithms [43]. The methods in the first three categories suffer from high time complexity and local minima trap, especially when mobile robots face multiple constraints when planning a path. Metaheuristic algorithms, a set of nature-inspired algorithms, are the fourth category in this taxonomy that imitate natural, biological, interactive behaviors or physical events [44,45]. These methods try to find an almost optimal path by eliminating the process of creating complex environment models based on stochastic approaches. The stochastic approaches can be efficient and fast in solving large and complex optimization problems, especially in non-differentiable, multi-objective, and multimodal problems [20,46].

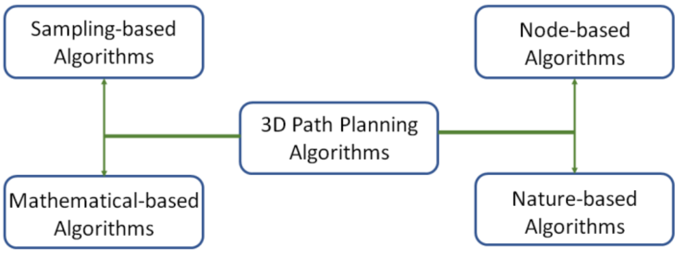

Figure 1. 3D path planning algorithms taxonomy [5,47].

Finding the best shortest path entails some problems such as the existence of many possible obstacles in its route. In addition, this path should be smooth without sharp turns and must consider movement restrictions. These problems may be even more cumbersome when considering large land areas and similar agricultural environments. Solution techniques in path planning algorithms for mobile autonomous mobile robots may include a visibility graph [48], probable road maps [49], and random exploring algorithms [50]. However, judging from the results of numerous studies in the literature, metaheuristic methods may be better overall [51–53]. Metaheuristic methods try to find an almost optimal path by eliminating the process of creating complex environment models based on stochastic approaches. These methods are among the most appropriate approaches to solve unifying and nonlinear global optimization problems [54]. Worth mentioning here is the No-Free-Lunch (NFL) [55] theorem. It asserts that there is no specific metaheuristic algorithm that provides the best solution for every optimization problem. This means that if one algorithm can solve a kind of problem effectively, then it may not be effective to solve another kind of problem. As such, there is a considerable demand to develop new metaheuristic algorithms that can be used in various problems.

As previously stated, the path planning problem has become popular in recent years and the metaheuristic algorithms can be the most appropriate solution for it, but in the literature, there are not many works that study agricultural lands for various purposes. Many agricultural studies in the literature have focused on issues such as the farmer's income from harvest, the variety of land use, the type and amount of employment, labor productivity, biodiversity indices based on landscape ecological measures, and soil erosion [56–58]. In the literature, although there are some studies on path planning in agricultures [59,60], they have generally not focused either on 3D path planning or on the problem of having many obstacles in the real environment farmlands and how to detect them.

In [61], the authors addressed the coverage path problem in a particular region with many known obstacles for mobile robots in agriculture. The study proposed a practical method, considering the geometry properties and obstacles of the area. It used an obstacle avoidance mechanism to find a coverage path for agricultural drones. However, optimal pathfinding and its usability in a 3D space were not taken into account. Additionally, the complexity time and space of their proposed method are not efficient in comparison with metaheuristic-based algorithms. In [59], the authors showed the simulation results of an algorithm designed to autonomously perform the path planning process for UAVs in agricultural lands. The purpose of this study was to provide the appropriate conditions to automate the process and carry out further audit activities. The algorithm considers photogrammetric parameters such as ground sample distance (GSD) and overlap between photos. For this, image processing techniques were used. In [62], the authors used autonomously acting ground robots for various agricultural applications. They researched different applications for path planning techniques to various agricultural contexts and applied land coverage and point-to-point navigation techniques. They used the D* to find the optimal path in a partial environment. However, this method is not very efficient since it uses a node-based algorithm (D* algorithm), and it is also designed for 2D areas [63]. As mentioned before, among the 3D path planning methods, metaheuristics may be the most efficient method. In [64], the authors proposed a custom model to navigate semi-autonomous agricultural robots with trailer. However, the geometry features were considered in 2D. In addition, the authors did not focus on finding the optimal path. Therefore, mobile devices moving on the non-optimal path map may not be successful in using their resources efficiently.

In [65], the authors proposed a path planning method inspired by the Ant Colony Optimization (ACO) algorithm to multipoint measurements in potato ridge cultivation. However, the related method did not perform successfully in finding optimal paths and is also useful for 2D areas. It may be unlikely to be implemented on real robots due to the fact that they did not focus on the recognition of obstacles and the avoidance of mechanisms of them. In [57], three local search metaheuristic algorithms, which were simulated by annealing and tabu search references, were used to calculate annual crop planning with a new irrigation mechanism. The objective function of this study was to maximize the gross benefits associated with the allocation of crops. The authors claimed that the tabu search method gave the best results in comparisons. In [66], an evolutionary algorithm was used for a complex strategic land use problem based on the management of a farming system. This study aimed to pursue a multi-purpose strategy that fulfilled spatial constraints in the 50-year planning management of the farm. Although the study is comprehensive, the metaheuristic method used and proposed may not be a very performant and efficient solution.

3. Materials and Methods

With the increase in the world population, the need for agricultural and food products has also increased. At the same time, the importance and need for smart agricultural systems and methods have also increased. Therefore, it is very important to plan optimal paths without harming objects (barriers) such as plants and trees in agricultural areas. Thanks to the methods proposed in this study, various tasks such as tracking crops in large farmlands can be performed efficiently by autonomous robots. Accordingly, it is necessary to find the optimal path between two points for robots without human intervention. Therefore, in this paper, two adaptive 3D path planning methods were presented for autonomous agricultural UAVs to find collision-free optimal paths in an acceptable time with the lowest process costs in different environments, containing various obstacles. These methods were developed, inspired by two metaheuristic algorithms (I-GWO and Ex-GWO). In addition, many obstacles were assumed to be present in the field in order to prove that the proposed methods are functional, and robots had to find their paths in relation to these obstacles. In addition, this study also used a mechanism for obstacle management. The studies in the literature either do not mention how to detect and prevent obstacles or they used the features of an existing device and did not suggest an algorithm or technique [20,64]. This mechanism can be embedded in various sensors and IoT devices.

3.1. Definitions

Before describing the proposed algorithms, the problem must be defined. The main purpose of 3D path planning is to find an optimum (or nearly optimal) path between the source (start) and the destination (target) stations. The path planning function is defined as outlined in Equation (1).

$$f(source,\ destination) \rightarrow Trajectory \quad (1)$$

Source and destination denote the relative coordinates of the source and destination positions on the map. Each path has a cost during movement from source to destination. There are different parameters used to define a cost between two points. In most studies, the cost is considered as the consumption of energy, Euclidean distance, and velocity [20,21]. For example, the position matrix determines how many stations robots travel from the source to destination. This matrix is defined using Equation (2).

$$Positions = [p_1\ , p_2, p_3, p_4 \ldots p_D] \quad (2)$$

where pi represents the position coordinates of each station that our robot takes on the map. In order to find an optimized trajectory, the proposed algorithms try to minimize cost (length of trajectory in our experiment). The cost of the trajectories is calculated using Equation (3), where *i* and *j* denote the current and next stations.

$$Cost_{(i,j)} = \sum_{i=s}^{j=D} distance_{i,j} + CurrentPower_i \quad (3)$$

Based on Equation (3), the cost of each founded path is obtained by the sum of distances between tuples from source to destination. Drones can be blended with metaheuristics so they can carry out their mission efficiently. In this regard, not only the distance parameters of the drones but also the remaining power amounts of drones are taken into account in the fitness function, which is defined to be more realistic. Therefore, the result from the metaheuristic algorithm can be used in real environments when applied to mobile robots. Random and optimized trajectories are used for UAV movement from source to destination, as shown in Figure 2. Here, the UAV moved through different stations. In path planning methods, usually, either the robots randomly move or costly processes are undertaken in finding an optimized path, but in this study, we tried to find the most efficient optimized path. This process is performed gradually between both stations. In this way, the UAV tries to find a path between two points. To optimize randomly created paths and to find the best possible trajectory, a method is proposed in this section with a minimum computational cost. Thanks to this method, robots can also actively avoid obstacles. In the final phase, the sum of all tuples' costs is calculated, and the cost of the path is obtained. The purpose of this study was to find the best path between the start and target stations of each UAV.

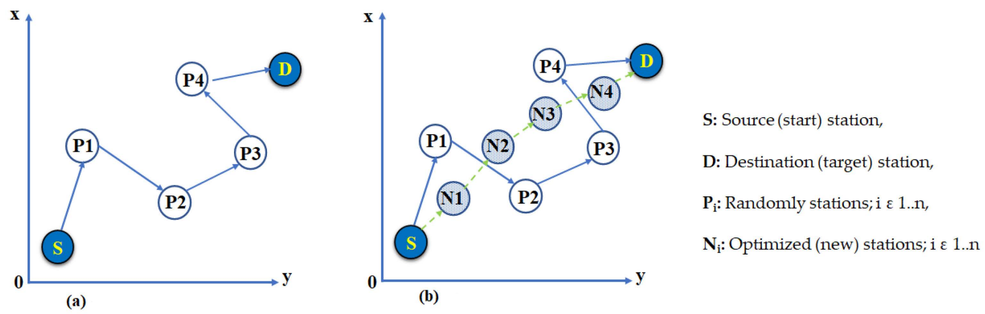

Figure 2. The randomly created and optimized trajectory. (**a**) Randomly Created Path; (**b**) Optimized Created Path.

Typically, the first step in path planning is to represent the workspace as a map. In the maps, many obstacles were used to make the mobile robots' tasks of finding the path realistic and complex. The challenge was to avoid various obstacles and to reach the position of the destination. In this study, a large-scale map was prepared to evaluate the proposed algorithms. The boundary of this map is shown in Figure 3a. In addition, three mobile robots with different start and destination stations were used, and their three-dimension points are given in Figure 3b. In this paper, it was assumed that the number of obstacles was quite high in order to make our proposed methods applicable in real areas. The number of obstacles was considered to be 150. Therefore, the coordination of some of the obstacles is presented in Figure 3c, and the full list is presented in Supplementary File 1. The problem of avoiding and managing obstacles is one of the most important aspects of path planning. The used mechanism includes two main steps and algorithms that take place sequentially, which were inspired by [47].

a) 3D map boundary

Map	Start boundary	End Boundary
Crowded Large map	(0, 0, 0)	(1000, 1000, 1000)

b) 3D map UAV initial and final positions

	UAV 1	UAV 2	UAV 3
Initial	(0, 0, 0)	(0, 500, 0)	(0, 1000, 0)
Final	(1000, 1000, 1000)	(1000, 500, 1000)	(1000, 0, 1000)

c) 3D obstacles for relevant map

Obstacles number	Crowded Large map	Obstacles number	Crowded Large map	Obstacles number	Crowded Large map
1	(10, 890, 0) - (40, 920, 15)	**11**	(180, 900, 0) - (210, 930, 15)	**21**	(60, 700, 0) - (90, 730, 15)
2	(30, 930, 0) - (60, 960, 15)	**12**	(200, 860, 0) - (230, 890, 15)	**22**	(110, 680, 0) - (140, 710, 15)
3	(70, 940, 0) - (100, 970, 15)	**13**	(160, 840, 0) - (190, 870, 15)	**23**	(160, 650, 0) - (190, 680, 15)
4	(160, 940, 0) - (190, 970, 15)	**14**	(210, 820, 0) - (240, 850, 15)	**24**	(50, 630, 0) - (80, 660, 15)
5	(110, 930, 0) - (140, 960, 15)	**15**	(170, 800, 0) - (200, 830, 15)	**25**	(30, 590, 0) - (60, 620, 15)
6	(60, 890, 0) - (90, 920, 15)	**16**	(130, 880, 0) - (160, 810, 15)	**26**	(80, 590, 0) - (110, 620, 15)
7	(30, 850, 0) - (60, 880, 15)	**17**	(120, 820, 0) - (150, 850, 15)	**27**	(120, 590, 0) - (150, 620, 15)
8	(80, 850, 0) - (110, 880, 15)	**18**	(90, 750, 0) - (120, 780, 15)	**28**	(200, 600, 0) - (230, 630, 15)
9	(100, 890, 0) - (130, 920, 15)	**19**	(80, 800, 0 - 110, 830, 15)	**29**	(160, 580, 0) - (190, 610, 15)
10	(140, 880, 0) - (170, 910, 15)	**20**	(40, 810, 0) - (70, 840, 15)	**30**	(220, 560, 0) - (250, 590, 15)

Figure 3. Land map (**a**), UAVs' positions (**b**) and obstacles coordinates (**c**).

3.2. GWO-Based Path Planning

In this paper, the path planning for autonomous agricultural robots was realized using the proposed method, inspired by Incremental Gray Wolf Optimization (I-GWO) and Expanded Gray Wolf Optimization (Ex-GWO) algorithms. These algorithms are inspired by gray wolves in nature. The natural behaviors of gray wolves such as encircling, hunting, and attacking prey have been modeled mathematically. Encircling in the I-GWO and Ex-GWO are calculated based on Equations (4) and (5). The hunting and attacking mechanism in the I-GWO can be obtained by Equations (9)–(11), and in the Ex-GWO, this is based on Equations (12)–(14). There are four types of wolves in each pack; alpha, beta, delta, and omega wolves. Each wolf has different responsibilities in the pack. Alpha, beta, and delta wolves are involved in encircling the prey, and omega wolves update their own positions based on them to attack the prey. The I-GWO algorithm is based on leader wolf's behavior. Other wolves in the pack update their own positions based on all the wolves selected before themselves. This may result in these wolves being present in similar regions. Thus, they only search for prey (solution) in a particular and similar area, which may be a missing point. The nth wolf in the pack updates its own position based on the $n-1$ wolf before it. This algorithm is completely dependent on the alpha wolf. In the I-GWO algorithm, all relative operations are addressed according to Equations (4)–(11), where t indicates the current iteration, T demonstrates maximum iteration number, $\vec{X}$ indicates the position vector of a wolf, and $\vec{X}_p$ is the position vector of the prey. Additionally, D is a vector that depends on the location of the target.

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p - \vec{X}_t \right| \tag{4}$$

$$\vec{X}(t+1) = \vec{X}_t - \vec{A} \cdot \vec{D} \tag{5}$$

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{6}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{7}$$

$$\vec{a} = 2\left(1 - \frac{t^2}{T^2}\right) \tag{8}$$

$$\vec{D}_\alpha = \left| \vec{C}_\alpha \cdot \vec{X}_\alpha - \vec{X} \right| \tag{9}$$

$$\vec{X}_\alpha = \vec{X}_\alpha - \vec{A}_\alpha \cdot \vec{D}_\alpha \tag{10}$$

$$\vec{X}_n(t+1) = \frac{1}{n-1} \sum_{i=1}^{n-1} X_i(t);\ n = 2,\ 3,\ \ldots m \tag{11}$$

Another metaheuristic algorithm (Ex-GWO) is based on the first three hierarchies of the wolves (alpha, beta, and delta) in a pack. The fourth level of the wolves in a pack update their positions based on the leading three wolves. Generally, the nth wolf updates its own position relative to the prey according to the previous and the first three wolves (Equations (12)–(14)). In the Ex-GWO algorithm, the attacking mechanism is used to avoid the prey from escaping.

$$\vec{D}_\alpha = \left| \vec{C}_1 \cdot \vec{X}_\alpha - \vec{X} \right|, \vec{D}_\beta = \left| \vec{C}_2 \cdot \vec{X}_\beta - \vec{X} \right|, \vec{D}_\delta = \left| \vec{C}_3 \cdot \vec{X}_\delta - \vec{X} \right| \tag{12}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha, \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta, \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \tag{13}$$

$$\vec{X}_n(t+1) = \frac{1}{n-1} \sum_{i=1}^{n-1} X_i(t);\ n = 4,\ 5,\ \ldots\ m \tag{14}$$

It is assumed that the coefficient vectors $\vec{A}$ and $\vec{C}$ lead to encircle the prey. The parameter $\vec{a}$ decreases from 2 to 0 relative to the iteration number. It is used to improve the convergence speed of the algorithm. These parameters control the tradeoff between exploration and exploitation phases. It is used to get closer to the solution range. $\vec{r}_1$ and $\vec{r}_2$ are the random vectors in a range of [0, 1]. In every algorithm, the leader encircles the prey, then hunts the prey, and finally attacks the prey based on the $\vec{A}$ value. If $\left|\vec{A}\right| < 1$, the wolf is attacking the prey; otherwise, it is busy trying to find prey (solution). Figure 4 depicts the working of the proposed algorithms, considering exploration and exploitation phases. Thanks to these features, the proposed 3D path planning methods were able to act in a balance between the two phases and try to find the most appropriate path without falling into any local optima trap.

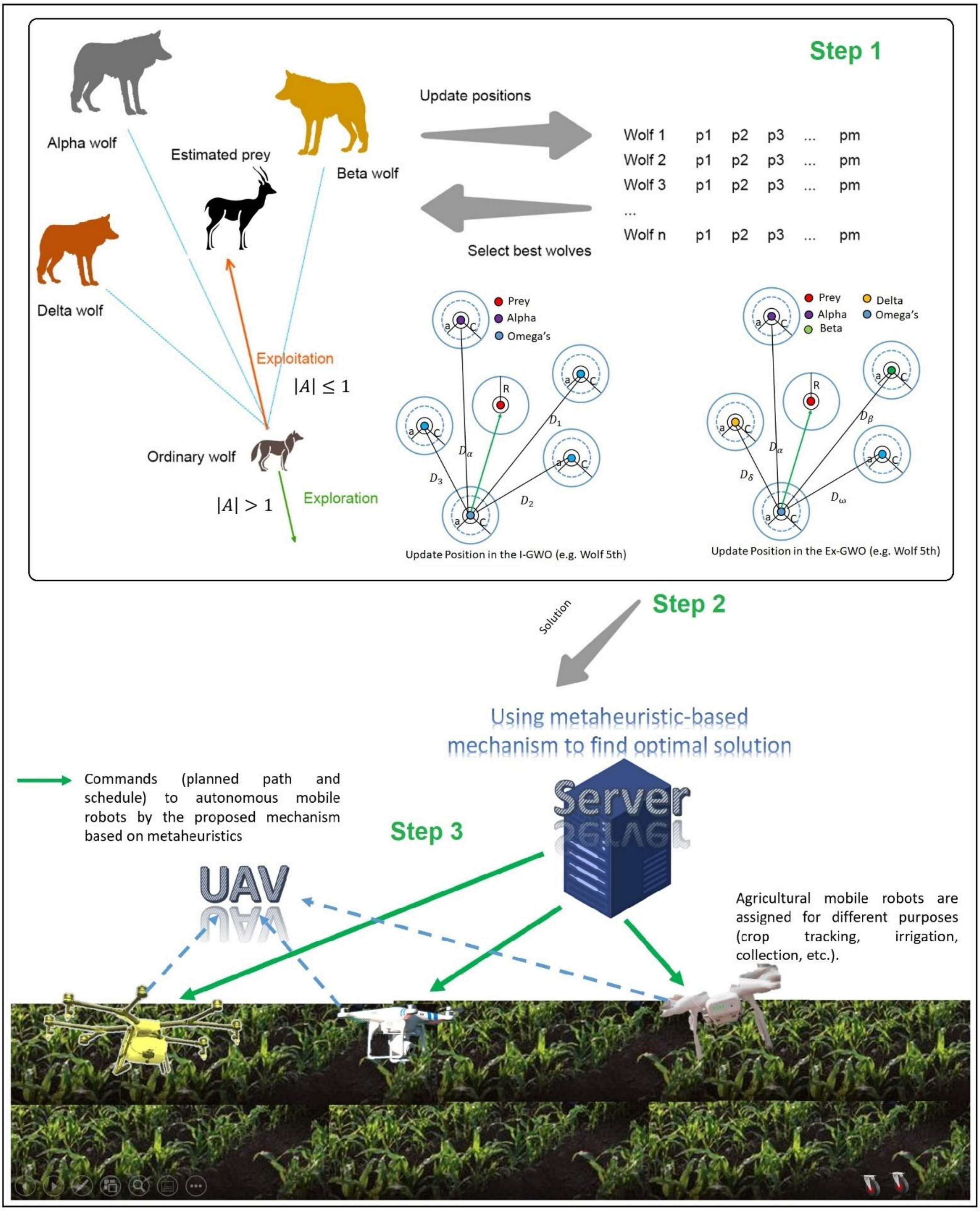

Figure 4. Working mechanism of the proposed method in UAV-based agricultural applications.

3.3. Working Mechanism of the Method

One of the most commonly applied methods of 3D path planning is to provide a robot with a defined number of static stations and to allow an algorithm to discover the most appropriate path. These types of algorithms are easier to apply mathematically, but generally, their time and space complexity is relatively higher. Here, a pool of stations is assumed so that these stations can be created randomly. Since the station selection in our methods is based on metaheuristic algorithms, it works appropriately with fewer parameters, and therefore, it can work efficiently by consuming resources in an acceptable time. Mathematically, this pool has been described in the structure of the 3xn matrix. The elements of search space represent distances between stations. Each station in the pool is a possible position that a mobile robot can choose as the next station. This pool is used to control the mobile robot's movement in the area. In addition, by using the information of this pool, it may be possible to help to avoid obstacles. The station selection process used in our methods is presented in Algorithm 1. In this study, the number and positions of stations (mobile robot stopovers) and obstacles are predefined similar to other studies in the literature [5,6,15,20,53]. On the other hand, obstacle avoidance is one of the many challenges that exist in the path planning problem. In this study, a method was used to avoid the collision of the UAVs with obstacles (objects or other robots), which benefits from geometric and calculus-based formulae. It was inspired by [47].

Algorithm 1. Pseudocode of station selection

1. State is array of candidate stations
2. w = distance obtained from metaheuristics //Equations (10) and (13)
3. d = The list of distances
4. **For** each station (i) in pool
5. di = distance between current and next stations + distance between next and destination stations
6. **End For**
7. MinDist = Min(d) //Min function indicates minimum distance in the list
8. **if** (MinDist < w)
9. Select station with minimum distance as next station
10. **Else**
11. Select station by metaheuristics as next station
12. **End if**

Primarily, the proposed methods initialize the random position matrix. Each row of the position matrix defines the path, and the columns represent the number of steps in the path to the destination. These number of stations are denoted as p. The (x_n^m, y_n^m, z_n^m) presents a coordinate of each station, where m is the aforementioned index of stations and n is the number of search agents in each method (Figure 5a). The search agents are the configuration parameter of the metaheuristic algorithms. Then, for each metaheuristic algorithm, a search space, based on the position matrix, is initialized. The search space is shown in Figure 5b, which represents the distance between tuples. In this table, each row represents a path length. Each element of the row shows the distance between two points as $d_{(i,j)}^n$, where i is the current state and j is the previous state. Furthermore, n is in the number of search agents. In addition, in the proposed methods, the path cost based on a fitness function that was presented in Equation (3) is calculated.

path	1	2	⋯	m
1	(x_1^1, y_1^1, z_1^1)	(x_1^2, y_1^2, z_1^2)	⋯	(x_1^m, y_1^m, z_1^m)
2	(x_2^1, y_2^1, z_2^1)	(x_2^2, y_2^2, z_2^2)	⋯	(x_2^m, y_2^m, z_2^m)
⋮	⋮	⋮	⋮	⋮
n	(x_n^1, y_n^1, z_n^1)	(x_n^2, y_n^2, z_n^2)	⋯	(x_n^m, y_n^m, z_n^m)

(a)

path	1	2	⋯	m
1	$d^1_{(1,s)}$	$d^1_{(2,1)}$	⋯	$d^1_{(D,m)}$
2	$d^2_{(1,s)}$	$d^2_{(2,1)}$	⋯	$d^2_{(D,m)}$
⋮	⋮	⋮	⋮	⋮
n	$d^n_{(1,s)}$	$d^n_{(2,1)}$	⋯	$d^n_{(D,m)}$

(b)

Figure 5. The working mechanism of the method. (**a**) The position matrix of each path; (**b**) the search space that represents distance between tuples.

In the next step, the proposed methods calculate the distance between each tuple for each station in the pool. In this case, we have a distance cost (d) between the current station and candidate next stations. The d includes two values: first is the distance between the current and next states, and the second is the distance between next and destination states. However, the metaheuristic algorithms find the best solution for the next station of each current station. If the distance of the possible next stations is smaller than the obtained value from metaheuristic algorithms (w), the relevant station with the minimum value is selected as the elected next station. Otherwise, the UAV chooses the achieved solution of the metaheuristic algorithms as the next station (Algorithm 1). The proposed method's aim is to reduce the cost of each path and try to find the optimal path with minimum cost for multi-UAVs. In this study, three UAVs were used that had dissimilar start (source) and final (destination) stations. The results obtained from this method are explained in the analysis and results section. The pseudocode and flowchart of the proposed path planning can be found in Algorithm 2 and Figure 6.

Algorithm 2. Pseudocode of proposed path planning

Initialize the grey wolf population X_i (i = 1, 2, ..., n)
Initialize A, C and a //*Equations(6)–(8)*
Initialize positions matrix and search space
Calculate fitness of each agent //*Equation (3)*
While (t < Max number of iterations)
  For each search agent
    Update the position of current search agent //*Algorithm 1.*
  End For
  Update a, A and C
  Calculate the fitness of all search agents
  Update position //*Equation (11) or Equation (14)*
  Update the search space matrix
  t = t +1
End While

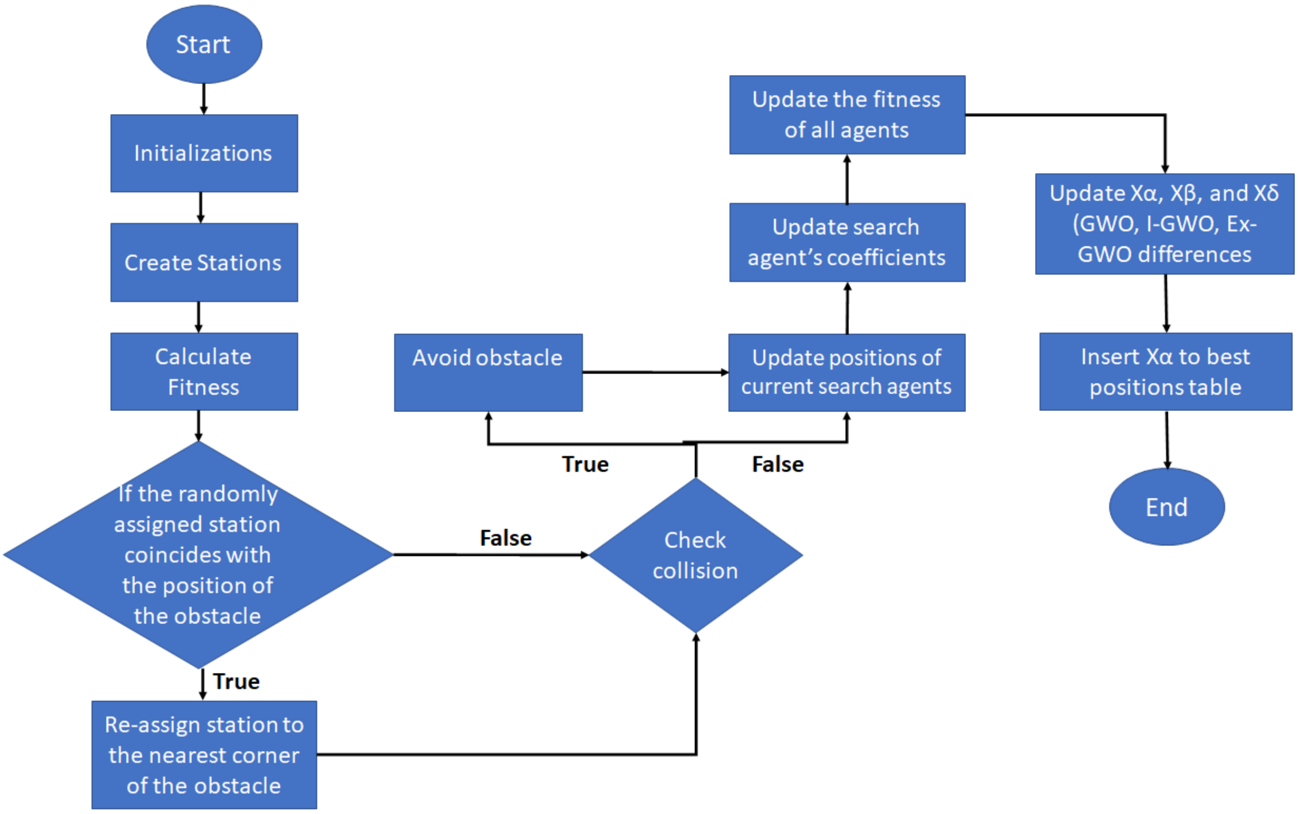

Figure 6. Proposed path planning method flowchart.

3.4. Other Possible Features: Applicability in Farmlands

Based on the functionality of farmland, farmers can analyze the data to increase productivity before the agricultural year begins. Most farmers fertilize their farmland based on the experimental information. Modern agriculture tries to use the source efficiently and encourages farmers to use new technologies in cultivation to increase productivity along with their income. While data that have been collected are stored in a light server to serve the clients, peer-to-peer communication can be held between monitoring devices with the robots via the Global System for Mobile communications (GSM). In precision agriculture, farmers are able to increase productivity by using the previous data analysis. As the connections are bidirectional, exchanging urgent commands such as changing tasks, terminating current tasks, and more can be performed. A tiny unit of computers of robots provides a mid-layer infrastructure to receive commands and to respond to requests. Thanks to the proposed algorithms, the farmer is able to lunch a UAV with predetermined states to monitor and control their land. Farmers can track the whole of their agricultural land and their crops remotely, and they can also meet their needs such as irrigation and harvesting using the related autonomous UAV and agricultural robot robots on an optimal path and minimum costs. In addition, the proposed methods can be used to find optimal routes for multiple UAVs at the same time in parallel or concurrently. In this case, each UAV perceives the other UAV as an obstacle andso, the relevant UAV can continue its mission without colliding with our obstacle management mechanism. In addition, thanks to this mechanism, it will be possible for the proposed methods to work successfully in dynamic or uncertain environments.

4. Results and Discussion

This section presents the performance of the proposed methods, which is analyzed and compared with the GWO-based 3D path planning method [20]. The authors used the Gray Wolf optimizer (GWO) algorithm to find an optimal path with minimal cost in 3D environments. According to the results of the study, in path planning, the GWO-based method is better than Dijkstra, A*, D*, and several famous metaheuristic-based methods. They proved that the GWO-based method presents a more balanced and better performance in similar problems. In addition, GWO-based algorithms are sought after in many research and application areas due to their balanced behavior amongst various metaheuristic algorithms [19,20]. Therefore, we selected this method for the comparison of results and performance. The implantation and analysis presentation was performed in Java and MATLAB. The algorithms proposed in this study were performed on a Core i7-5500 U 2.4 processor with 8GB of RAM.

4.1. Simulation Setting

In the simulation, large-scale, agricultural land was considered. The size of the environment was 1000 m ∗ 1000 m ∗ 1000 m. In addition, 150 obstacles were also placed in this area. Three UAVs with different start and endpoints were considered in each simulation of the used methods. The map boundaries, UAVs, and obstacle positions were assumed based on Figure 3. Each used algorithm was run 15 times. Furthermore, simulation parameters are presented in Table 1. The best, worst, and average costs (distance traveled in meters), execution times and complexity, and finally, convergence curve analysis for each UAV in each algorithm was applied by different population sizes and iteration numbers.

Table 1. The simulation parameters.

Parameter	**Value**
Population size	30, 50, 100
Maximum iteration	50, 100, 200
Farmland Square	1000 m ∗ 1000 m ∗ 1000 m
r_1, r_2	Rand [0,1]
a	linearly decreased from 2 to 0 over
A	[−2a, 2a]
C	Rand [0, 2]

4.2. Analysis and Evaluation (Cost of Paths)

In this section, the proposed path planning methods are analyzed based on the cost function, introduced in Equation (3). The results obtained are presented in Table 2. The starting and ending points of UAVs are assumed to be different from each other. In this table, the costs for these autonomous robots were obtained from a set of various populations and iterations. This process was evaluated for all algorithms used. According to the results obtained, the Ex-GWO-based method achieved the best result compared to other used path planning methods. The Ex-GWO-based method gave the best solution in five of the assumed nine scenarios and ranked first among the three methods with a 55.56% success rate. In the ranking, the I-GWO-based method was second with 38.88% and the GWO-based method was third with 5.56%. These results are presented in Table 3.

Table 2. Simulation results for each path planning algorithm on crowded large-scale map.

Algorithm	Pop	Iter	UAV_1 (Cost-m)			UAV_2 (Cost-m)			UAV_3 (Cost-m)			Overall Simulation Time (s)
			Best	*Ave*	*Worst*	*Best*	*Ave*	*Worst*	*Best*	*Ave*	*Worst*	
GWO	30	50	**2199**	2645	3385	2019	2328	2566	2148	2611	3526	**8.416**
I-GWO	30	50	**2199**	2736	3290	2087	2378	2579	**2107**	2446	2723	11.747
EX-GWO	30	50	2250	2649	3205	**1996**	2314	2655	2156	2713	4195	9.910
GWO	50	100	2145	2573	3295	1955	2234	2497	2095	2526	3469	**15.040**
I-GWO	50	100	2181	2558	3119	1993	2321	2520	**2090**	2361	2662	17.654
EX-GWO	50	100	**2128**	2621	3121	**1918**	2238	2593	2102	2638	4139	16.686
GWO	100	200	2070	2522	3202	1870	2136	2403	2026	2453	3417	**23.378**
I-GWO	100	200	**2045**	2537	3047	1936	2223	2466	2016	2261	2588	26.659
EX-GWO	100	200	2088	2479	2983	**1858**	2186	2528	**2007**	2568	4065	24.794

* The best values are bold.

Table 3. Ranking summary of metaheuristic algorithms in cost parameter.

Algorithm	Success Rate (Percent)	Rank
GWO	5.56	3
I-GWO	38.88	2
Ex-GWO	**55.56**	**1**

Based on the obtained results, it is determined that the Ex-GWO-based method exhibits good performance in large-scale and complex farmland with a high number of obstacles. This is because the Ex-GWO-based method finds the best solution according to the alpha, beta, delta wolves, and whole pack. The wolves use the whole pack's location knowledge to update their positions, so for experiments with larger population sizes and more iterations, the Ex-GWO-based method has a better chance of reaching the best solution. Therefore, the wolves in the pack minimize the escape paths of the hunt (prey), and hence, the prey can be caught faster. The fact that this mechanism can be better than other methods can be seen more clearly in large and crowded environments. On the other hand, another method proposed in this study, the I-GWO-based path planning method, outperforms good results in smaller and less populated environments. The basic update process in this method is very dependent on the alpha setup. Therefore, the speed of growth and the selection of the right places for the first wolf is of great importance. In this method, there is the possibility of finding problem solutions (prey) much faster in fewer iterations. For this reason, our proposed methods may be the most appropriate choices in various real-life application areas of mobile autonomous systems such as the use of UAVs for different and varied purposes and environments. In general, the GWO-based method has good performance in medium, small-sized, and not too crowded environments. In fact, the usage capacity of it may be between our two methods, but its success rate is not considered good according to the results. Briefly, the Ex-GWO-based path planning method may be performed more successfully in larger and crowded environments with larger populations and more iterations, and the I-GWO-based path planning method may give good results in medium and smaller, less populated environments.

Additionally, in Figure 7, the movements of UAVs for each algorithm are also shown on the defined map based on the obtained simulation results in various population sizes and iterations. In this figure, the circles show the start state of each UAV, and the star symbols show the destination state of each UAV.

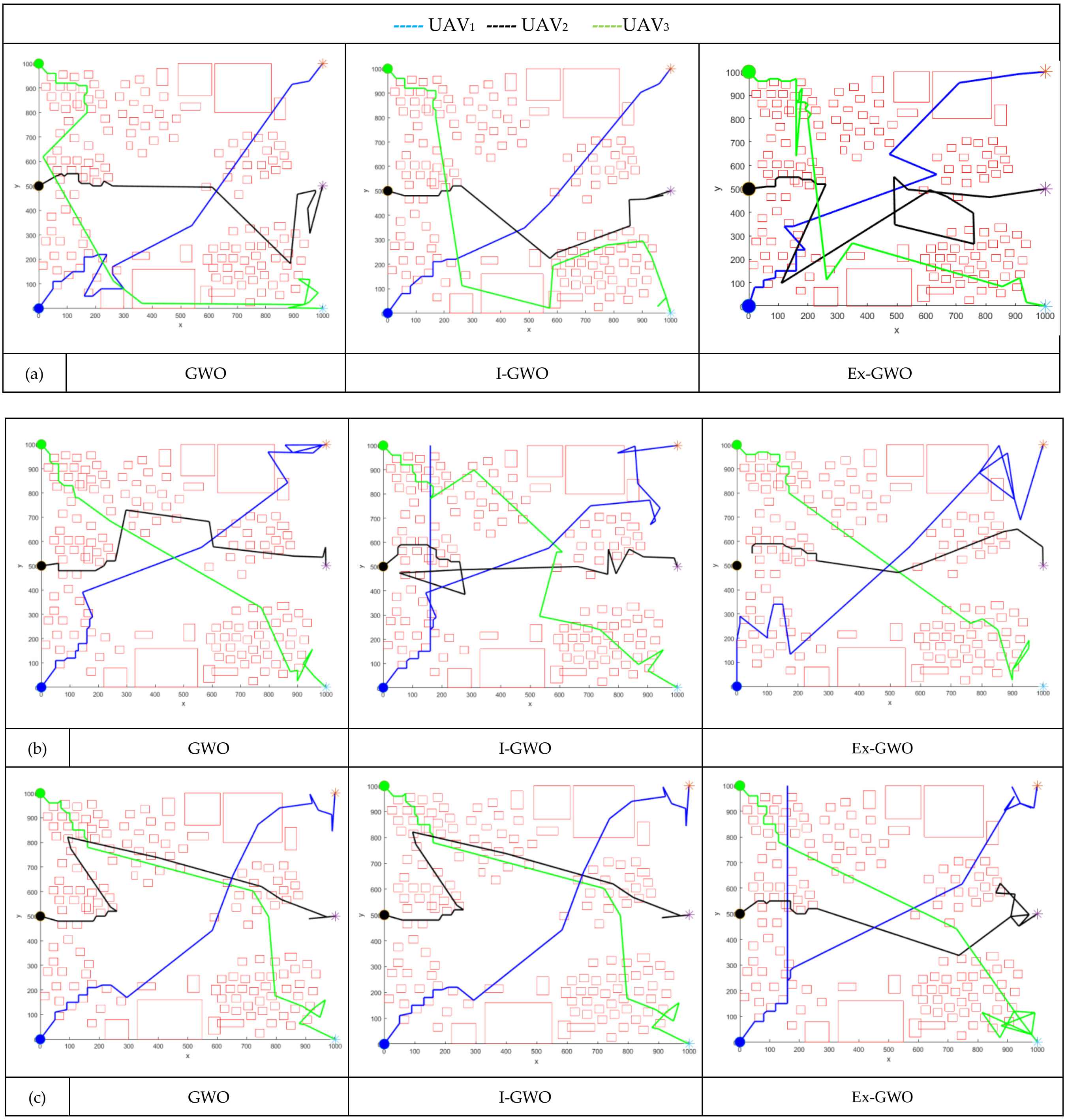

Figure 7. The movement of UAVs on the generated paths in each method. (**a**) population of 30, 50 iterations; (**b**) population of 50, 100 iterations; (**c**) population of 100, 200 iterations.

4.3. Analysis and Evaluation (Taken Times and Complexity)

The execution times of the proposed methods are also taken into consideration. The best execution time analyses for each method are presented in Figure 8 for various population sizes and iterations. The GWO has the best overall-time performance, while Ex-GWO and I-GWO rank second and third, respectively. Indeed, the GWO-based path planning for three UAVs in the parallel periods consumes the minimum time to reach its destination. The reason for this may be due to the fact that it depends on the three first wolves. In the I-GWO, the incorrect position or the wrong movement of the alpha wolf can move the whole pack away from the target or cause them to catch the prey late. At the Ex-GWO, each pack member has more roles and contributions than the other two methods, which means that this algorithm may need a longer execution time. However, the Ex-GWO may not be the worst in terms of time, as seen with its better performance in crowded environments. The results show that in the crowded map scenarios with many barriers, the I-GWO-based method does not perform well with regard to the overall time and optimum path cost. The fact that the GWO had the best overall time does not mean that the other two methods were bad, because these two methods could be concluded in an acceptable time. In addition, the time complexity analysis of the proposed methods is $O(n^2)$.

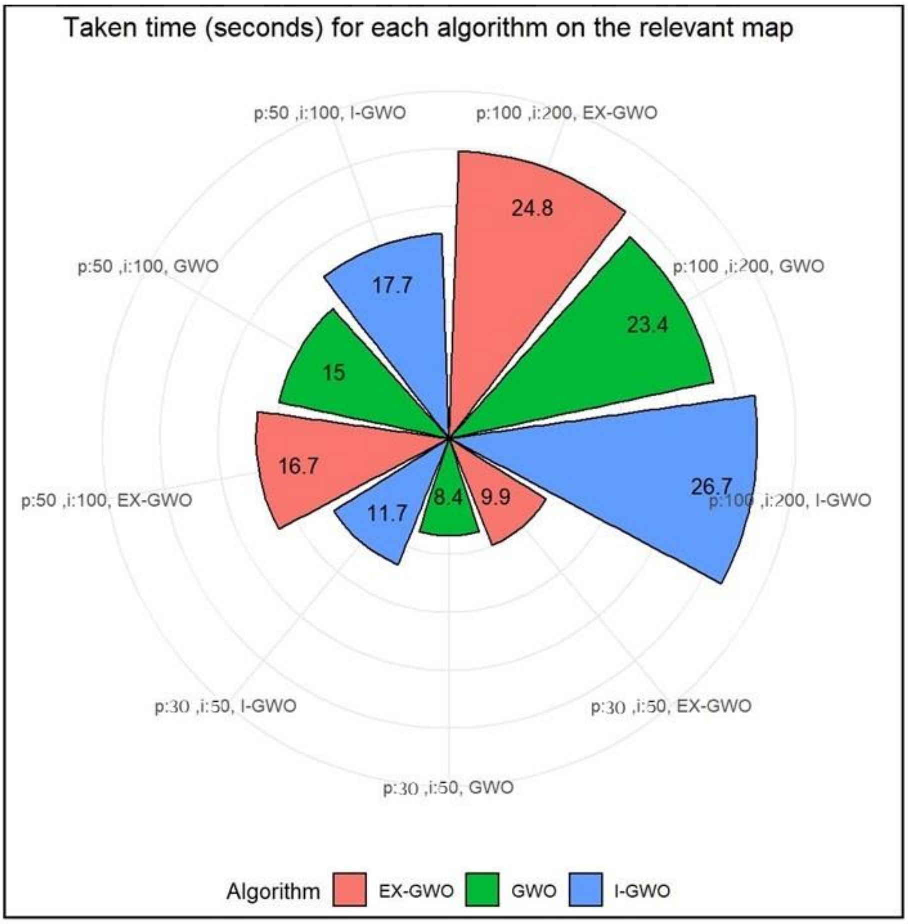

Figure 8. Taken time for each method on the relevant map.

4.4. Analysis and Evaluation (Convergence Curve)

Figure 9 presents the convergence curve of each proposed path planning algorithm. As mentioned before, the number of obstacles and the boundary sizes of the map are listed in Figure 3. The three metaheuristic algorithms used have different structures in the exploration and exploitation phases. Figure 9 illustrates the convergence curve of each method with various iterations and population sizes. In the I-GWO algorithm, the transition from exploration to the exploitation phase is faster than the other two metaheuristic algorithms (GWO and Ex-GWO). As a result of the observations, it was concluded that 50 iterations were enough to analyze of convergence rate because the results achieved did not display remarkable differences [20].

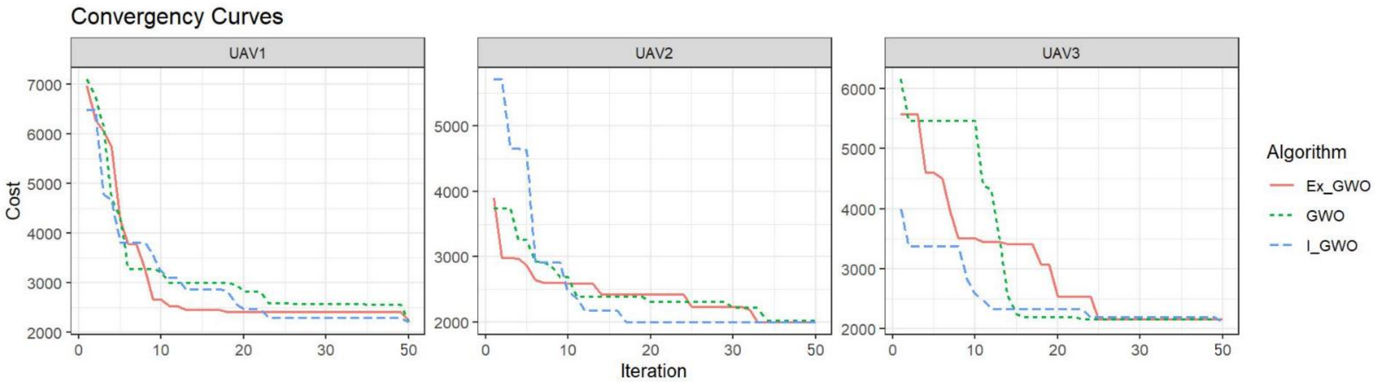

Figure 9. Convergence analysis for each UAV on the relevant map in population of 30 and 50 iterations.

In Figure 10, the statistical results of the path planning methods with the boxplot graph are presented. Boxplots are a standard method for displaying data distribution based on statistical indicators such as minimum, first quartile (Q1), median, third quartile (Q3), and maximum. This diagram also provides information regarding the existence of outlier data. In addition, the symmetry ratio in the data can be analyzed from this graph. The values were obtained from three metaheuristic algorithms with a population size of 30 and 50 iterations after 15 runs. The box plot graph analysis describes the maximum and minimum values of the obtained best cost and the frequency of the values. The *x*-axis of each figure indicates the name of the respective algorithm, whereas the *y*-axis indicates the average of best cost obtained. From Figure 10, it can be observed that the results obtained using the Ex-GWO algorithm are near to the best solution, whilst the algorithm tries to find the best solution. As well as this, after initial iterations in the exploitation phase the Ex-GWO obtained results near to the best cost.

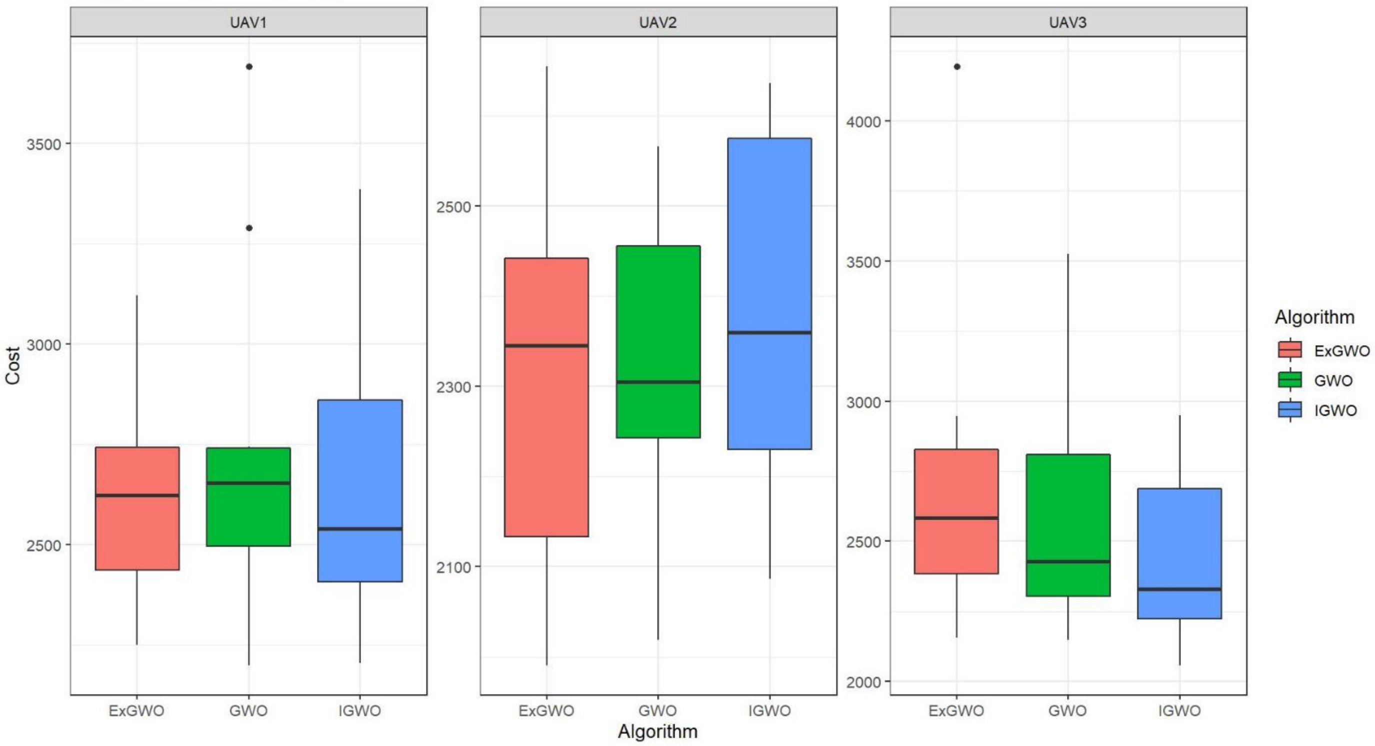

Figure 10. Boxplot graph analysis for each UAV in population of 30 and 50 iterations.

Figure 11 illustrates the distributions of costs in 15 runs. While the UAV_2 has an almost uniform distribution, both UAV_1 and UAV_3 have lower cost densities. Note that obstacles are employed as a marker for these metaheuristic algorithms, and paths with an appropriate number of obstacles help to improve the performances. For this purpose, a Student's t-test was applied for all combinations of UAVs. The p-value of UAV_1 and UAV_2 for all combinations of algorithms, population, and iterations count in 15 runs is 9.3×10^{-12}, the p-value of UAV_1, and UAV_3 is 0.201, and the p-value of UAV_2 and UAV_3 is 9.8×10^{-6}. Generally, p-values less than 0.05 are accepted for hypothesis rejection. The null hypothesis is that all UAV s do not have a meaningful relationship. The significant difference between UAV_2 with both UAV_1 and UAV_3 is proved. Therefore, the null hypothesis is rejected.

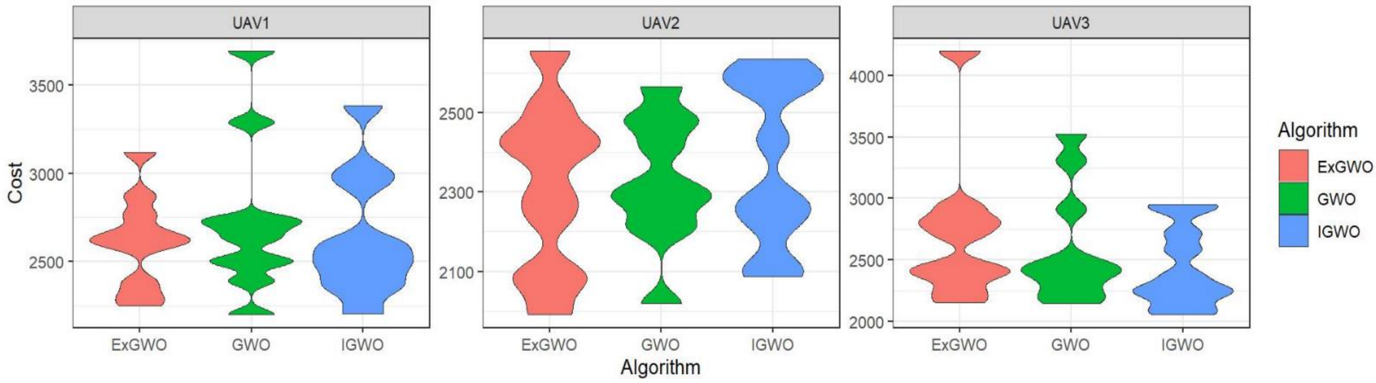

Figure 11. Distributions of costs in 15 runs for each UAV in population of 30 and 50 iterations.

5. Conclusions

The focus of the paper was to solve the NP-hard problem of efficient crop harvesting by finding the most suitable and optimal paths for UAVs. This study presented adaptive 3D path planning methods using metaheuristic algorithms (I-GWO and Ex-GWO) for autonomous agricultural UAVs. Therefore, in this study, maximum profit was achieved by consuming the least energy by harvesting the most crops in the shortest possible time. In addition, the use of resources such as human and natural resources was carried out efficiently by creating sustainable and smart agriculture. In other words, the method allows farmers to monitor crop variability and stress conditions continuously and harvest the best crops, resulting in efficient resource consumption and an increase in profits. The proposed methods tried to find the best solution in an acceptable time without falling into any local optima trap. The proposed method's aim was to reduce the cost of each path and try to find the optimal path with the minimum cost for multi-UAVs. In addition, this study also proposed a mechanism for obstacle management. In this study, a large-scale farmland map with many various obstacles was considered. From the results, it can be concluded that in terms of the minimum execution time parameter, the GWO-based method did the best, whereas in finding the optimal path with the minimum cost, the Ex-GWO-based method was better. The proposed method based on the Ex-GWO attained a 55.56% success rate, the I-GWO, and the GWO-based method attained 38.88% and 5.56% success rates in optimal path costs, respectively. In addition, in the analysis of convergence curve behavior for metaheuristic algorithms, the proposed I-GWO-based method was observed to offer the best solution. Thanks to the algorithms proposed in this study, efficient resource consumption and product growth rate can be achieved with low risk and cost. They can also be used in real agricultural applications. In addition, the consideration and installation of specific mechanical and hardware devices to mobile robots and farmland can play an important role. In this regard, information about the mission environment can be gathered by other types of sensors (e.g., laser spot), which are mounted on mobile UAVs. These sensors can provide information about the shape, size, and location of an obstacle. Using sensory information, robots may advance towards a target without colliding with an obstacle or coming under enemy radars. On the other hand, various sensor devices are used to collect information on parameters such as humidity, temperature, etc. in agricultural land for different applications. Briefly, since the map information and the starting and destination points of each mobile device are certain, the developed method can be easily embedded on these devices. Thanks to the obstacle and object detection feature used of the method, the supposed parameters in the defined fitness function, and the station selection feature on the map, method can be applicable in the real world as well. It can also be even more useful when combined with special equipment used in farmland and mobile devices.

In future studies, we would like to explain our roadmap below with a focus on smart and sustainable agriculture. Alongside mobile robots, it will focus on a method that tracks and harvests crops in large-scale farmland with Internet of Vehicles (IoVs). In such a scenario, the mobile robots would only be tasked with monitoring the farmland. In this case, a blended mechanism with image processing methods will be presented. It will then use the results from these autonomous robots as an input matrix for the IoVs. Since a complex and NP-hard type of problem will arise here, metaheuristic-based algorithms will again come into play. In this regard, hybrid or new algorithms will be presented. On the other hand, the 3D path planning methods proposed in this study can be applied to IoT systems such as smart cities, industries, and agriculture in hybrid form with machine learning algorithms such as reinforcement-learning- or game-theory-based algorithms.

Supplementary Materials: The supporting information about maps can be downloaded at: https://www.mdpi.com/article/10.3390/app12030943/s1.

Author Contributions: Conceptualization, F.K., S.N. and F.A.A.; methodology, F.K., T.Ç., F.C. and A.S.; software, A.S. and S.N.; validation, A.S., S.N., G.R., S.L., A.M.; formal analysis, A.S., F.C. and S.N.; investigation, A.S., F.A.A. and F.C.; resources, F.K., F.C., T.Ç., A.M. and A.S.; data curation, A.S. and S.N.; writing—original draft preparation, F.K., A.S., F.C., G.R., S.L. and A.M.; writing—review and editing, F.K., S.N., T.Ç., F.A.A., G.R., S.L. and A.M.; visualization, A.S., F.C., G.R., S.L. and A.M.; supervision, F.K., A.M. and S.N.; project administration, F.K.; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data will be made available from the corresponding author on reasonable request.

Conflicts of Interest: The authors declare that they have no conflict of interest.

References

1. United Nations Environment Programme. Sustainability. Available online: https://www.unep.org/about-un-environment/sustainability (accessed on 29 September 2021).
2. Sylvester, G. *E-Agriculture in Action: Drones for Agriculture*; Food and Agriculture Organization of the United Nations and International Telecommunication Union: Bangkok, Thailand, 2018; pp. 11–22.
3. Dehghan Khangahi, F. Ecological Problems and Social Mobilization: The Case of Urmia Lake. Ph.D. Thesis, Istanbul University, Istanbul, Turkey, 2020.
4. Dehghan Khangahi, F.; Kiani, F. Social Mobilization and Migration Predictions by Machine Learning Methods: A study case on Lake Urmia. *Int. J. Innov. Technol. Explor. Eng.* **2021**, *10*, 123–127. [CrossRef]
5. Yang, L.; Qi, J.; Song, D.; Xiao, J.; Han, J.; Xia, Y. Survey of Robot 3D Path Planning Algorithms. *J. Control Sci. Eng.* **2016**, *2016*, 7426913. [CrossRef]
6. Yang, L.; Qi, J.; Xiao, J.; Yong, X. A literature review of UAV 3D path planning. In Proceeding of the 11th World Congress on Intelligent Control and Automation, Shenyang, China, 29 June–4 July 2014; pp. 2376–2381. [CrossRef]
7. Agrawal, H.; Dhall, R.; Iyer, K.S.S.; Chetlapalli, V. An improved energy efficient system for IoT enabled precision agriculture. *J. Ambient. Intell. Humaniz. Comput.* **2020**, *11*, 2337–2348. [CrossRef]
8. Kiani, F.; Nematzadehmiandoab, S.; Seyyedabbasi, A. Designing a dynamic protocol for real-time Industrial Internet of Things-based applications by efficient management of system resources. *Adv. Mech. Eng.* **2019**, *11*, 1–23. [CrossRef]
9. Kiani, F.; Seyyedabbasi, A.; Nematzadeh, S. Improving the performance of hierarchical wireless sensor networks using the metaheuristic algorithms: Efficient cluster head selection. *Sens. Rev.* **2021**, *41*, 368–381. [CrossRef]
10. Tzounis, A.; Katsoulas, N.; Bartzanas, T.; Kittas, C. Internet of Things in agriculture, recent advances and future challenges. *Biosyst. Eng.* **2017**, *164*, 31–48. [CrossRef]

11. Nayyar, A.; Nguyen, B.-L.; Nguyen, N.G. The Internet of Drone Things (IoDT): Future Envision of Smart Drones. In *First International Conference on Sustainable Technologies for Computational Intelligence*; Advances in Intelligent Systems and Computing; Springer: Singapore, 2020; Volume 1045, pp. 563–580.
12. Anastasios, L.; Thomas, L.; Panagiotis, S.; Michalis, Z.; George, L. Towards smart farming: Systems, frameworks and exploitation of multiple sources. *Comput. Netw.* **2020**, *172*, 107147.
13. Verónica, S.; Francisco, R. From Smart Farming towards Agriculture 5.0: A Review on Crop Data Management. *Agronomy* **2020**, *10*, 207.
14. Kiani, F.; Seyyedabbasi, A. Wireless Sensor Network and Internet of Things in Precision Agriculture. *Int. J. Adv. Comput. Sci. Appl.* **2018**, *9*, 99–103. [CrossRef]
15. Benos, L.; Bechar, A.; Bochtis, D. Safety and ergonomics in human-robot interactive agricultural operations. *Biosyst. Eng.* **2020**, *200*, 55–72. [CrossRef]
16. Panagiotis, R.; Panagiotis, S.; Thomas, L.; Ioannis, M. A compilation of UAV applications for precision agriculture. *Comput. Netw.* **2020**, *172*, 107148.
17. Kadeghe, G.; Wesley, M.; Edward, M.; Glen, C. An Extensive Review of Mobile Agricultural Robotics for Field Operations: Focus on Cotton Harvesting. *AgriEngineering* **2020**, *2*, 150–174.
18. Dewangan, R.K.; Shukla, A.; Godfrey, W.W. Three dimensional path planning using Grey wolf optimizer for UAVs. *Appl. Intell.* **2019**, *49*, 2201–2217. [CrossRef]
19. Seyyedabbasi, A.; Kiani, F. I-GWO and Ex-GWO: Improved algorithms of the Grey Wolf Optimizer to solve global optimization problems. *Eng. Comput.* **2021**, *37*, 509–532. [CrossRef]
20. Seyyedabbasi, A.; Kiani, F. MAP-ACO: An efficient protocol for multi-agent pathfinding in real-time WSN and decentralized IoT systems. *Microprocess. Microsyst.* **2020**, *79*, 103325. [CrossRef]
21. Chung, H.M.; Maharjan, S.; Zhang, Y.; Eliassen, F.; Strunz, K. Placement and Routing Optimization for Automated Inspection with Unmanned Aerial Robots: A Study in Offshore Wind Farm. *IEEE Trans. Ind. Inform.* **2020**, *17*, 3032–3043. [CrossRef]
22. del Cerro, J.; Cruz Ulloa, C.; Barrientos, A.; de León Rivas, J. Unmanned Aerial Robots in Agriculture: A Survey. *Agronomy* **2021**, *11*, 203. [CrossRef]
23. Macrina, G.; Di Puglia Pugliese, L.; Guerriero, F.; Laporte, G. Drone-aided routing: A literature review. *Transp. Res. Part C Emerg. Technol.* **2020**, *120*, 102762. [CrossRef]
24. Baik, H.; Valenzuela, J. An optimization drone routing model for inspecting wind farms. *Soft Comput.* **2021**, *25*, 2483–2498. [CrossRef]
25. Allred, B.; Eash, N.; Freeland, R.; Martinez, L.; Wishart, D. Effective and efficient agricultural drainage pipe mapping with UAS thermal infrared imagery: A case study. *Agric. Water Manag.* **2018**, *197*, 132–137. [CrossRef]
26. Vasudevan, A.; Kumar, D.A.; Bhuvaneswari, N.S. Precision farming using unmanned aerial and ground robots. In Proceedings of the IEEE Technological Innovations in ICT for Agriculture and Rural Development (TIAR), Chennai, India, 15–16 July 2016; pp. 146–150.
27. Behjati, M.; Noh, A.M.; Alobaidy, H.; Zulkifley, M.; Nordin, R.; Abdullah, N. LoRa Communications as an Enabler for Internet of Drones towards Large-Scale Livestock Monitoring in Rural Farms. *Sensors* **2021**, *21*, 5044. [CrossRef] [PubMed]
28. Chowdhury, S.; Shahvari, O.; Marufuzzaman, M.; Li, X.; Bian, L. Drone routing and optimization for post-disaster inspection. *Comput. Ind. Eng.* **2021**, *159*, 107495. [CrossRef]
29. Dukkanci, O.; Kara, B.Y.; Bektaş, T. Minimizing energy and cost in range-limited drone deliveries with speed optimization. *Transp. Res. Part C Emerg. Technol.* **2021**, *125*, 102985. [CrossRef]
30. Felegari, S.; Sharifi, A.; Moravej, K.; Amin, M.; Golchin, A.; Muzirafuti, A.; Tariq, A.; Zhao, N. Integration of Sentinel 1 and Sentinel 2 Satellite Images for Crop Mapping. *Appl. Sci.* **2021**, *11*, 10104. [CrossRef]
31. Matrice, D. Matrice 100. 100, 2016, 2017. Available online: https://www.dji.com/product/matrice100 (accessed on 14 November 2021).
32. Papachristos, C.; Kamel, M.; Popović, M.; Khattak, S.; Bircher, A.; Oleynikova, H.; Dang, T.; Mascarich, F.; Alexis, K.; Siegwart, R. Autonomous Exploration and Inspection Path Planning for Aerial Robots Using the Robot Operating System. In *Studies in Computational Intelligence*; Koubaa, A., Ed.; Springer Science and Business Media LLC: Toledo, Spain, 2018; pp. 67–111.
33. Christiansen, M.P.; Laursen, M.S.; Jørgensen, R.N.; Skovsen, S.; Gislum, R. Designing and Testing a UAV Mapping System for Agricultural Field Surveying. *Sensors* **2017**, *17*, 2703. [CrossRef] [PubMed]
34. Faical, B.S.; Pessin, G.; Filho, G.P.; Carvalho, A.C.; Furquim, G.; Ueyama, J. Fine-Tuning of UAV Control Rules for Spraying Pesticides on Crop Fields. In Proceedings of the 2014 IEEE 26th International Conference on Tools with Artificial Intelligence, Limassol, Cyprus, 10–12 November 2014; pp. 527–533.
35. Dai, B.; He, Y.; Gu, F.; Yang, L.; Han, J.; Xu, W. A vision-based autonomous aerial spray system for precision agriculture. In Proceedings of the 2017 IEEE International Conference on Robotics and Biomimetics (ROBIO), Macao, China, 5–8 December 2017; pp. 507–513.
36. Klauser, F.; Pauschinger, D. Entrepreneurs of the air: Sprayer drones as mediators of volumetric agriculture. *J. Rural. Stud.* **2021**, *84*, 55–62. [CrossRef]
37. Skobelev, P.; Budaev, D.; Gusev, N.; Voschuk, G. Designing Multi-agent Swarm of UAV for Precise Agriculture. In *International Conference on Practical Applications of Agents and Multi-Agent Systems*; Javier, B.J., Ed.; Springer: Toledo, Spain, 2018; pp. 47–59.

38. Ju, C.; Son, H.I. Multiple UAV Systems for Agricultural Applications: Control, Implementation, and Evaluation. *Electronics* **2018**, *7*, 162. [CrossRef]
39. Li, X.; Zhao, Y.; Zhang, J.; Dong, Y. A Hybrid PSO Algorithm Based Flight Path Optimization for Multiple Agricultural UAVs. In Proceedings of the 2016 IEEE 28th International Conference on Tools with Artificial Intelligence (ICTAI), San Jose, CA, USA, 6–8 November 2016; pp. 691–697.
40. Noreen, I.; Khan, A.; Habib, Z. Optimal Path Planning using RRT*-Adjustable Bounds. *Intell. Serv. Robot* **2018**, *11*, 41–52. [CrossRef]
41. Guruji, A.K.; Agarwal, H.; Parsediya, D. Time-efficient A* Algorithm for Robot Path Planning. *Procedia Technol.* **2016**, *23*, 144–149. [CrossRef]
42. Jason, G.; Xin, M.; Liu, F.; Ying, W.; Ren, H. Mathematical Modeling and Intelligent Algorithm for Multi-Robot Path Planning. *Math. Probl. Eng.* **2017**, *2017*, 1465158.
43. Li, J.; Yang, S.X.; Xu, Z. A Survey on Robot Path Planning using Bio-inspired Algorithms. In Proceedings of the 2019 IEEE International Conference on Robotics and Biomimetics (ROBIO), Dali, China, 6–8 December 2019; pp. 2111–2116.
44. Choudhury, N.; Mandal, R.; Kar, S.K. Bioinspired robot path planning using PointBug algorithm. In Proceedings of the 2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT), Chennai, India, 3–5 March 2016; pp. 2638–2643.
45. Wu, L.; Li, Y.; Liu, J. Based on Improved Bio-Inspired Model for Path Planning by Multi-AUV. In Proceedings of the Proceedings of the 2018 International Conference on Electronics and Electrical Engineering Technology, Tianjin, China, 19–21 September 2018; pp. 128–134.
46. Seyyedabbasi, A.; Aliyev, R.; Kiani, F.; Gulle, M.U.; Basyildiz, H.; Shah, M.A. Hybrid algorithms based on combining reinforcement learning and metaheuristic methods to solve global optimization problems. *Knowl.-Based Syst.* **2021**, *223*, 107044. [CrossRef]
47. Kiani, F.; Seyyedabbasi, A.; Aliyev, R.; Gulle, M.U.; Basyildiz, H.; Shah, M.A. Adapted-RRT: Novel hybrid method to solve three-dimensional path planning problem using sampling and metaheuristic-based algorithms. *Neural Comput. Appl.* **2021**, *33*, 15569–15599. [CrossRef]
48. Flemming, S.; la Anders, C.H.; Morten, B. Configuration Space and Visibility Graph Generation from Geometric Workspaces for UAVs. In Proceedings of the AAIA, Guidance, Navigation, and Control Conference, Portland, OR, USA, 8–11 August 2011; pp. 1–12.
49. Bera, T.; Bhat, M.S.; Ghose, D. Analysis of Obstacle based Probabilistic RoadMap Method using Geometric Probability. *IFAC Proc. Vol.* **2014**, *47*, 462–469. [CrossRef]
50. Kavraki, L.; Svestka, P.; Latombe, J.-C.; Overmars, M. Probabilistic roadmaps for path planning in high-dimensional configuration spaces. *IEEE Trans. Robot. Autom.* **1996**, *12*, 566–580. [CrossRef]
51. Kiani, F.; Seyyedabbasi, A.; Aliyev, R.; Shah, M.A.; Gulle, M. 3D Path Planning Method for Multi-UAVs Inspired by Grey Wolf Algorithms. *J. Internet Technol.* **2021**, *22*, 1–12.
52. Pandey, P.; Shukla, A.; Tiwari, R. Three-dimensional path planning for unmanned aerial robots using glowworm swarm optimization algorithm. *Int. J. Syst. Assur. Eng. Manag.* **2018**, *9*, 836–852. [CrossRef]
53. Qu, G.; Gai, W.; Zhong, M.; Zhang, J. A novel reinforcement learning based grey wolf optimizer algorithm for unmanned aerial robots (UAVs) path planning. *Appl. Soft Comput. J.* **2020**, *89*, 1–12. [CrossRef]
54. Wolpert, D.H.; Macready, W.G. A comparison of deterministic and probabilistic optimization algorithms for nonsmooth simulation-based optimization. *Build. Environ.* **2004**, *39*, 989–999. [CrossRef]
55. Wolpert, H.; William, G. No free lunch theorems for optimization. *IEEE Trans. Evol. Comput.* **1997**, *1*, 67–82. [CrossRef]
56. Cantelli, L.; Bonaccorso, F.; Longo, D.; Melita, C.D.; Schillaci, G.; Muscato, G. A Small Versatile Electrical Robot for Autonomous Spraying in Agriculture. *AgriEngineering* **2019**, *1*, 29. [CrossRef]
57. Chetty, S.; Adewumi, A.O. Three New Stochastic Local Search Metaheuristics for the Annual Crop Planning Problem Based on a New Irrigation Scheme. *J. Appl. Math.* **2013**, *2013*, 158538. [CrossRef]
58. Memmah, M.-M.; Lescourret, F.; Yao, X.; Lavigne, C. Metaheuristics for agricultural land use optimization. A review. *Agron. Sustain. Dev.* **2015**, *35*, 975–998. [CrossRef]
59. Palomino-Suarez, D.; Pérez-Ruiz, A. Towards Automatic UAV Path Planning in Agriculture Oversight Activities. In *LACAR 2019: Advances in Automation and Robotics Research*; Springer: Cali, Colombia, 2019; pp. 22–30.
60. Zeng, J.; Ju, R.; Qin, L.; Hu, Y.; Yin, Q.; Hu, C. Navigation in Unknown Dynamic Environments Based on Deep Reinforcement Learning. *Sensors* **2019**, *19*, 3837. [CrossRef] [PubMed]
61. Wang, K.; Meng, Z.; Wang, L.; Wu, Z.; Wu, Z. Practical Obstacle Avoidance Path Planning for Agriculture UAVs. In *IEA/AIE 2019: Wotawa F. Advances and Trends in Artificial Intelligence. From Theory to Practice*; Springer: Graz, Austria, 2019; pp. 196–203.
62. Juman, M.A.; Wong, Y.W.; Rajkumar, R.K.; H'Ng, C.Y. An integrated path planning system for a robot designed for oil palm plantations. In Proceedings of the TENCON 2017—2017 IEEE Region 10 Conference, Penang, Malaysia, 5–8 November 2017; pp. 1048–1053.
63. Santos, L.C.; Santos, F.N.; Pires, E.S.; Valente, A.; Costa, P.; Magalhães, S. Path Planning for ground robots in agriculture: A short review. In Proceedings of the 2020 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC), Azores, Portugal, 15–17 April 2020; pp. 61–66.

64. Pichler-Scheder, M.; Ritter, R.; Lindinger, C.; Amerstorfer, R.; Edelbauer, R. Path planning for semi-autonomous agricultural robots. In *Reinventing Mechatronics*; Yan, X.T., Ed.; Springer: Cham, Switzerland, 2020; pp. 35–53.
65. Mai, T.; Shao, S.; Yun, Z. The Path Planning of Agricultural AGV in Potato Ridge Cultivation. *Ann. Adv. Agric. Sci.* **2019**, *3*, 32003. [CrossRef]
66. Chikumbo, O.; Goodman, E.; Deb, K. Approximating a multidimensional Pareto front for a land use management problem: A modified MOEA with an epigenetic silencing metaphor. In Proceedings of the 2012 IEEE Congress on Evolutionary Computation (CEC), Brisbane, Australia, 10–15 June 2012; pp. 1–9.