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ANT ALGORITHM APPLICATION FOR ROUTE PLANNING FOR UNMANNED AERIAL VEHICLES (UAVs)

Abstract. Creating routes for drones is a convoluted process hence this objective requires to design optimal itineraries for safe interaction between groups of remotely piloted aerial systems (RPAS). Also, drone exploitation opens up completely new perspectives in logistic control systems because, in comparison with a ground vehicle, RPAS uses airspace as its primary road flying directly to the designated point. However, it must be maintained that a such small aircraft is vulnerable to weather conditions and does not have an excessive amount of energy which a drone operator always has to keep in mind when he intends to take off. Thereby, the problem of route design consists of numerous restrictions and demands optimal algorithms for efficient navigation.

The article is devoted to the actual problem of using unmanned aerial vehicles in human activity. In particular, the article considers the task of routing unmanned aerial vehicles, which is a complex optimisation problem involving the determination of optimal routes for a group of UAVs to perform various tasks. The subject environment of the problem is characterised, which may include the following components: unmanned aerial vehicle, objects and recharging stations. It describes several existing analogues of platforms that can be used for route planning using unmanned aerial vehicles, in particular DJI Terra and Altitude Angel. The authors consider the most common types of vehicle route optimisation problems (Capacitated Vehicle Routing Problem, VRP with Time Windows, Multiple Depot VRP). The paper formulates a mathematical statement of the UAV routing problem.

Considerable attention is paid to the ant algorithm and its modifications. The authors define the importance and prospects for further research on the use of heuristic algorithms for controlling semi-automated systems.

Keywords: routing task, ant algorithm, UAVs.

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ЗАСТОСУВАННЯ МУРАШИНОГО АЛГОРИТМУ ПЛАНУВАННЯ МАРШРУТІВ ДЛЯ БЕЗПЛОТНИХ ЛІТАЛЬНИХ АПАРАТІВ

Анотація. Задача маршрутизації БПЛА є складною задачею оптимізації, що передбачає визначення оптимальних маршрутів для групи безпілотних апаратів. Використання БПЛА у логістиці відкриває нові перспективи, зокрема завдяки встановленню різноманітних датчиків зображення та можливостям реального часу передачі даних. На відміну від традиційних транспортних засобів, БПЛА можуть прямувати безпосередньо між пунктами призначення, використовуючи повітряні простори. Однак, при плануванні маршрутів необхідно враховувати метеорологічні умови та обмежений запас палива. Відтак, задача маршрутизації БПЛА включає в себе численні обмеження і потребує розробки оптимальних алгоритмів для ефективного управління польотами.

Стаття присвячена актуальній проблемі використання безпілотних літальних апаратів в діяльності людини. Зокрема, розглянуто задачу маршрутизації безпілотних літальних апаратів, що являє собою складну оптимізаційну проблему, яка включає визначення оптимальних маршрутів для групи БПЛА з метою виконання різноманітних завдань. Охарактеризоване предметне середовище задачі, яке може включати такі складові елементи: безпілотний повітряний апарат, об'єкти та станції перезарядки.

Описано декілька існуючих аналогів платформ, які можуть бути використані для планування маршрутів з використанням безпілотних літальних

апаратів, зокрема DJI Terra та Altitude Angel. Розглянуто найбільш поширені види задач оптимізації маршрутів транспортних засобів (Capacitated Vehicle Routing Problem, VRP with Time Windows, Multiple Depot VRP). Сформульовано математичну постановку задачі маршрутизації БПЛА. Значна увага в статті приділена мурашиному алгоритму та його модифікаціям. Визначено важливість та перспективи подальших досліджень, щодо використання евристичних алгоритмів для керування напів автоматизованими системами.

Ключові слова: задача маршрутизації, алгоритми мурашиних колоній, БПЛА.

The problem statement. Ukraine, along with other countries, is at a stage of intense technological transformation where innovative decisions play a major role in solving present challenges. Modernity has already shown how useful drones are for overcoming various issues such as firefighting missions and giving the most accurate and reliable dataset possible. Their technical advantages allow them to conduct search and rescue missions during hazardous situations such as landslides, floods, or any other types of natural catastrophes. UAVs have quick access to hard-to-reach sites and share vital info for rescue teams in real-time mode.

The drone use practice involves a monitoring of transport infrastructure giving a chance to detect potential problems like traffic jams, distress in energy supply, and environmental pollution in advance. Their usage positively impacts on approvals of really needed decisions in urbanization, traffic management, and sustainability.

UAVs can also be used to inspect infrastructure such as bridges, highways, power lines, etc. They provide the ability to detect potential problems or damage, allowing for timely repairs and maintaining the safety and reliability of the infrastructure.

UAVs can monitor inventory, detect identification tags, and control the condition and location of goods in warehouses to automate and improve inventory management. This helps to accurately and efficiently manage inventory, reduce wastage, and streamline ordering and delivery processes.

The use of unmanned aerial vehicles in monitoring hydrocarbon fields is becoming an increasingly relevant and effective solution. UAVs can be equipped with a variety of sensors that can collect data on the state of the fields, including temperature, pressure, soil and atmospheric composition, gas concentration, etc. Due to their ability to easily enter hard-to-reach areas, they can cover a large area of the field and provide fast and accurate monitoring.

The purpose of the article is to consider the most popular types of vehicle route optimisation problems and algorithms based on the behaviour of ants.

Summary of the main material. The task of routing unmanned aerial vehicles (UAVs) is a complex optimisation problem that involves determining the optimal routes for a group of UAVs to perform various tasks. UAVs open up new

opportunities for improving logistics in various environments. Due to the installation of various image sensors, UAVs are able to capture images of objects, transmitting the received images in real time to the control station via wireless data transmission. Particular attention should be paid to their ability to move around without the need to use the main network.

Recent technological advances, such as longer battery life, improved communication devices, and lower production costs, have led to the growing use of UAVs in various fields. In contrast to traditional ground vehicles that are forced to follow specific routes, UAVs can move directly between destinations using airspace. It should be noted, however, that when planning routes, consideration should be given to the impact of meteorological conditions such as strong winds, fog, rain or snow, which may limit the ability to fly safely. In addition, UAVs have a limited fuel supply, which limits their ability to perform long missions or cover long distances [1].

The subject matter environment may include the following elements:

1. An Unmanned Aerial Vehicle (UAV) is a physical vehicle used to collect data and perform missions. UAVs can come in a variety of sizes and types, including drones, long-endurance aircraft, and others.
2. Objects are places that need to be visited or flown over using unmanned aerial vehicles. These objects can have different functional purposes, such as video and photo capture, information gathering locations, and search and rescue areas.
3. Recharging stations are points designed to recharge UAV energy sources such as batteries or fuel tanks. These stations allow UAVs to connect to a charging or refuelling station to continue their flight.

We consider several existing analogues of platforms that can be used for route planning using unmanned aerial vehicles (UAVs).

DJI Terra is software created by DJI for aerial image processing and UAV route planning. Released in April 2018, it is specifically designed for use with DJI UAVs.

DJI Terra has advanced functionality that allows you to create accurate 3D models, mapping data and orthophoto plans based on aerial images taken with DJI UAVs. The software also offers route optimisation capabilities to minimise time.

DJI Terra uses a variety of algorithms to optimise routes, taking into account factors such as UAV speed, flight restrictions, terrain and other parameters. The user can configure various route parameters such as flight altitude, image overlap, and image spacing, and the software will automatically calculate the best route to collect data in the shortest amount of time.

The optimised route allows you to efficiently collect the data you need and minimise the time required to complete the mission. In addition, DJI Terra provides visualisation and analysis capabilities for the data obtained, which allows it to be used in geospatial applications and solutions [2].

Altitude Angel is an airspace management and drone routing platform. It offers a variety of solutions, including drone registration and identification, routing based on airspace and environmental constraints, flight monitoring and control, and integration with other systems and services, such as navigation and weather services.

One of the key advantages of the Altitude Angel platform is its ability to automatically optimise drone routes, ensuring the most efficient flight paths with minimal time and energy. It takes into account various factors, such as airspace restrictions, the location of other aircraft, restricted areas, and other parameters to ensure safe and efficient drone flights.

The Altitude Angel platform also allows for integration with other systems and services to create end-to-end drone mission management solutions. It allows drone operators to plan routes, set flight restrictions and requirements, monitor flight safety, and interact with other airspace users [3].

One of the most studied and challenging areas of combinatorial optimisation is the development of routes for vehicles. In certain market segments, transport costs can account for a significant share of the total cost of goods, so the use of effective optimisation tools can lead to a significant reduction in overall costs. Over the past decades, numerous surveys and studies have been conducted on this problem and its variations.

In real-life scenarios, there are many different constraints that need to be taken into account when planning routes. Therefore, there are different types of vehicle route optimisation problems. For example, there may be restrictions on driving time, vehicle carrying capacity, the number of customers to be served, their delivery time requirements, etc. Different types of vehicle routing problems are created depending on which constraints need to be taken into account. In addition, different types of problems can have different optimisation objectives, such as minimising time, fuel costs or the number of vehicles used.

Vehicle route optimisation tasks can be classified according to various criteria. The main ones are:

- Number of vehicles: routing tasks can be solved for one or more vehicles.
- Number of delivery points: there may be tasks with one or more depots.
- Limitations on the number of points a vehicle can visit: in some cases, the number of points a vehicle can visit may be limited.
 - Time constraints: there may be routing tasks with time constraints, for example, if you need to deliver goods in a limited time.
 - Symmetry: problems can be symmetrical if the distance between any two points on the route is the same in both directions.
 - Traffic type: routing tasks can be solved for vehicles moving from point to point or back and forth.

This classification makes it possible to highlight the main aspects of vehicle routing problems and helps in the development of effective algorithms for solving them [4].

We consider the most common types of vehicle routing optimisation problems.

Capacitated Vehicle Routing Problem (CVRP): it involves the optimisation of vehicle routes based on their congestion. The main constraint is the maximum weight of goods that can be transported by each vehicle on each route up to a certain value. All vehicles have the same capacity. CVRP is often used to optimise freight transport, where it is important to efficiently distribute the load between vehicles, minimise fuel costs and delivery time.

VRP with Time Windows: this task optimises vehicle routes based on time constraints known as 'time windows'. Each delivery address is assigned a specific time interval during which the delivery must be made. This avoids unnecessary waiting and ensures that the goods are delivered to customers on time. VRP with Time Windows is especially useful for urban logistics systems, where it is important to make deliveries according to the schedule and minimise delays [5].

Multiple Depot VRP is the task of optimising the routes of vehicles with multiple depots. In this case, service operators are served from several different bases, as opposed to the classic VRP problem, where the delivery route starts and ends at one base. In order to solve this problem, it is necessary to distribute customers to different bases that have their own vehicle fleet. Vehicles start their route from the corresponding base, serve the customers assigned to this base, and then return back. The Multiple Depot VRP solution is of great importance for companies and organisations that have a distributed customer base or different logistics centres. Multiple Depot VRP is widely used in such areas as logistics, distribution, courier services, and e-commerce [5].

The problem of routing unmanned aerial vehicles is often referred to in the modern literature as the problem of optimising the routes of vehicles with multiple depots. The aim of these tasks is to build an optimal route through a given set of objects while minimising the total distance or duration of flights. The conditions must be met that each facility will be visited by only one UAV, and all facilities must be included in the route and only once. Since the objects are only visited without the need to deliver cargo, this means that there is no restriction on the carrying capacity [6].

We formulate the mathematical statement of the UAV routing problem described in the previous section.

Input data is:

- s - an average speed of UAV
- t - a UAV charge time
- T - a maximum time of UAV in the air without a spare recharging

Given a set consisting of n objects of the UAV's flight $A = \{0, 1, \dots, (n - 1)\}$ and a set of recharging stations $C = \{c_1, c_2\}$. We also have a matrix of distances between objects, including recharging stations $d_{lm} = \{l, m \in \{0, 1, \dots, (n + 1)\}\}$. Variables n and $(n + 1)$ are equal to charge stations c_1 and c_2 respectively. The matrix

of time needed to come over the object is done with respect to the matrix of distance $\{d_{lm}\}$ and average speed UAV s : $r_{lm} = \{l, m \in \{0, 1, \dots, (n+1)\}\}$. The task is to determine the plan of visiting the objects, which consists of B routes, where B is a value that is unknown at first, but is determined during the solution. The first route of the UAV starts from the station c_1 and ends at any of the two stations C , the next route of the UAV starts from the station where it recharged.

This way, the set of objects to be flown A should be divided into B ordered subsets:

$$\{A_1 = \{a_0^1, a_1^1 \dots a_{n_1-1}^1\}, \dots, A_B = \{a_0^B, a_1^B \dots a_{n_B-1}^B\}\}, \quad (3.1)$$

$$\text{If } \bigcup_{b=1}^B A_b = A \quad (\sum_{b=1}^B (n-1)_b = (n-1)), \quad (3.2)$$

$$A_i \cap A_j = \emptyset, \text{ де } i \neq j. \quad (3.3)$$

The above conditions guarantee that each object will be included in the route, but only in one route of the flight plan and only once:

$$A_1 = \{a_0^1, a_1^1 \dots a_{n_1-1}^1\} - \text{objects included in the first route,}$$

$$A_B = \{a_0^B, a_1^B \dots a_{n_B-1}^B\} - \text{objects included in last route } B.$$

Provided that none of the subsets of objects contains recharging stations. The subsets of objects are separated by visits to recharging stations. First, the UAV departs from the first station. After it visits each of the object subsets, the UAV flies to the first or second station to recharge. The UAV finishes when it has visited all the subsets of objects at the second or first station.

We assume R_b as the total time spent on route processing b ($b = 1, \dots, B$):

$$R_1 = r_{c_1, a_0^1} + \sum_{i=0}^{n_1-1} r_{a_i^1, a_{i+1}^1} + r_{a_{n_1-1}^1, C}, C \in \{c_1, c_2\}, \quad (3.4)$$

$$R_b = r_{C, a_0^b} + \sum_{i=0}^{n_b-1} r_{a_i^b, a_{i+1}^b} + r_{a_{n_b-1}^b, C}, b = 1, \dots, B, C \in \{c_1, c_2\}. \quad (3.5)$$

Based on the meaningful description of the problem, the objective function was defined to minimise the total time required to fly over all objects, including the time required to recharge at the stations:

$$z = (B-1)t + \sum_{b=1}^B R_b \rightarrow \min \quad (3.6)$$

This objective function minimises the number of routes included in the flight plan, taking into account the time required for recharging, the number of recharges and thus the number of routes included in the solution.

The total time spent on visiting all the objects on each route, including ending at one of the stations, should not exceed the time-limited potential of the UAV:

$$R_b \leq T, \text{ where } b = 1, \dots, B, \quad (3.7)$$

where

$$R_b = \sum_{l=0}^{n+1_b} \sum_{m=0}^{n+1_b} r_{lm}. \quad (3.8)$$

The constraint that ensures that a plan for visiting objects consists of one or more routes is as follows:

$$B \geq 1 \quad (3.9)$$

The structure of the solution will be as follows:

$$c_1, a_0^1, a_1^1, \dots, a_{n_1-1}^1, C, \dots, C, a_0^B, a_1^B, \dots, a_{n_B-1}^B, C,$$

where $C = \{c_1, c_2\}$.

The problem of unmanned aerial vehicle routing is a well-known complex combinatorial optimisation task. It requires finding optimal routes. In practical applications, difficulties arise in designing and managing the system's distribution, as several operational constraints are imposed on route construction.

Exact methods for solving routing problems are based on mathematical models and algorithms that allow finding the optimal solution to the problem. These methods are the most accurate and reliable, as they guarantee that an optimal solution will be found. On the other hand, they have limitations when applied to large problems, as they can require significant computing resources and take a long time to solve complex problems. Therefore, exact methods are most often used to solve smaller problems, where their advantages in accuracy and guaranteed optimal solution outweigh computational complexity [8].

Approximate methods are algorithms that quickly provide a solution to a routing problem, but cannot guarantee an optimal solution. These methods use heuristic or metaheuristic approaches to solve the problem. They can be useful in cases where an exact solution is too costly in terms of time or resources [7].

In the context of routing problems, heuristic methods refer to algorithms that use expert knowledge and empirical rules to find approximate or optimal solutions. Heuristic methods are divided into constructive, two-phase, and improving methods.

Constructive is a type of algorithm for solving transport routing problems. These methods are used to create an initial solution for a VRP problem, which can then be improved using other algorithms, such as improvement methods. The basic idea of design methods is to start with an empty route and successively add customers to the route until the constraint on the number of customers that can be served by one vehicle is satisfied.

Two-phase (clustering) methods usually consist of two main steps:

Clustering phase: In this phase, the input data is divided into subsets (clusters) of variables and constraints. The partitioning can be done according to different criteria, for example, to group variables that have similar properties, or to group constraints that have a similar structure.

Optimisation phase: This stage, each cluster is solved separately, and solutions are found for each cluster. This can be done using different solution methods.

Improvement methods are algorithms that are aimed at improving an existing solution by finding a better solution with a lower cost. The basic idea of improvement methods is to make small changes to an existing solution to obtain an optimal one.

These small changes often consist of changing the order of customers between routes, changing the order of customers within a route, or changing the sequence of routes. The purpose is to find the optimal route sequence that satisfies all constraints and minimises the total cost [9].

Metaheuristic methods use a combination of local and global solution search and combine them into abstract strategies for heuristic problem optimisation.

Local search algorithms are iterative methods that are based on searching for partial solutions among the points in the vicinity of the current point at each iteration. Instead of a full search, local search is used in subsets of options called neighbourhoods. In transport routing problems, local search can be used to improve solutions found by different heuristic algorithms.

Population-based methods take inspiration from natural concepts, such as species evolution and the behaviour of social insects that search for food. These methods implement a high-level control strategy based on various memory structures, such as neural networks, solution pools represented as chromosomes, or pheromone matrices. Furthermore, all known successful heuristics for this type of routing problem also rely on local search components to guide the search towards promising solutions. In summary, most population-based methods in the literature are hybrid, meaning that they combine different approaches and components from other methods. This allows them to take advantage of the advantages of each individual approach and ensures efficient and balanced performance in different tasks. [8].

Ant colonies and other insect social societies are distributed systems characterised by a highly organised social structure, despite the simplicity of the individuals. They can perform complex tasks that exceed the individual capabilities of individual ants.

The field of ‘ant algorithms’ explores models derived from observations of real-world ant behaviour and uses them as inspiration for the development of new optimisation and distributed control algorithms. The basic idea is that the principles of self-organisation provided by the highly organised behaviour of real ants can be used to coordinate artificial agents in solving computational problems.

Ant colonies have inspired the creation of various types of ant algorithms that include food search, division of labour, and cooperative transport. In all of these examples, ants coordinate their activities through stigmergy, an indirect way of communicating that is carried out through modifications to the environment. For example, a searcher ant uses chemicals to leave tracks on the ground, increasing the likelihood that other ants will follow the same path. Biologists have shown that many aspects of the social behaviour of ant colonies can be explained using simple models that involve only stigmatic communication. In other words, researchers have shown that often stigmatic, indirect communication is sufficient to explain how social insects achieve self-organisation.

This idea is at the core of ant algorithms and is used to coordinate artificial societies of agents. There are many successful examples of ant algorithms, one of which is the Ant Colony Optimiser (ACO), which specialises in solving discrete optimisation problems. In this approach, unexpected discoveries from the food-finding behaviour of real ants have been applied to create artificial ants that can solve complex optimisation problems.

Thus, ant algorithms use the principles of self-organisation and stigma to coordinate the actions of societies of artificial agents. They demonstrate that simple rules of interaction between agents can lead to effective solutions to complex optimisation problems. These algorithms open up new possibilities for developing simulation models and algorithms that use natural principles of coordination and collective intelligence to solve real-world problems [10].

We consider the most common types of ant colony algorithms.

Ant Colony System - improves the classical AS algorithm by using the information accumulated by previous generations to improve the probabilistic model of the search process. This is achieved through two processes.

First of all, it is the use of an exclusively priority selection strategy when updating the pheromones that ants leave on edges, i.e. the pheromone is changed only on those edges that belong to the best solution found by the ants.

Secondly, the ants select the next node to be included in the partial solution, using the pseudo-random proportional selection rule.

At the stage of pheromone updating, after the end of the activity of each generation of ants, it is stored exclusively in the ant that found the best solution.

The ant colony system also uses an online step-by-step update of the ants' chemicals, which helps to reduce the likelihood of choosing the same routes by all members of the population [8].

In MMAS, all pheromone values are initially set to the maximum value. As ants move along edges, they deposit pheromone depending on the quality of the solution. However, the pheromone deposited is limited by the maximum and minimum constraints defined by the algorithm.

At each iteration, a global update is performed to adjust the pheromone levels on the edges. The best ant of an iteration deposits additional pheromone on the edges of the best solution found up to that point. This pheromone amplification on the best solution helps to direct the search to promising regions of the solution space [11].

Elitist Ant System - this algorithm introduces a certain number of 'elite' ants into the population. These elite ants have the ability to deposit a larger amount of pheromone on the edges they pass compared to ordinary ants.

The main objective of including elite ants is to increase the efficiency of the potentially promising solutions that have been identified so far. By actively depositing more pheromone on the edges of the best paths, the algorithm directs its efforts to find and concentrate around these high-quality solutions.

The presence of elite walls in the population improves the convergence rate of the algorithm, as they prefer to exploit well-proven solutions. That being said, it is important to strike a balance between exploration and exploitation. If too many elite walls are introduced, it may cause premature convergence and the algorithm may get stuck in local optima. On the other hand, too few elite walls can lead to insufficient exploration of the search space [10].

Ant-Q - L. Gambardella and M. Dorigo wrote a study that was published in 1995. In this paper, they presented an improvement of the ant colony algorithm, proposing its interpretation as a system capable of learning. This method got its name from machine learning and incorporated many ideas from it.

In this algorithm, each edge is assigned a value that indicates its suitability for transition. The value of the utility of transition along an edge is calculated based on the values of the utility of transition through the following edges, which were determined during the previous identification of possible next states. These values are stored in a Q-table, in other words, the data is modified and updated during the algorithm's operation [12].

Conclusions. Ant algorithms are based on imitating the self-organisation of social insects through the use of dynamic mechanisms by which the system achieves a global goal as a result of local low-level interaction of elements. The effectiveness of other algorithms increases with the dimensionality of the optimisation problem. The results of other optimisation ants are especially good for non-stationary systems whose parameters change in time, such as telecommunication and computer networks. An important property of ant algorithms is non-convergence: even after a large number of iterations, many solution options are simultaneously explored, which results in no long time delays in local extremes. All this allows us to recommend the use of ant algorithms for solving complex combinatorial optimisation problems. Perspective ways to improve ant algorithms are on-line adaptation of parameters using a fuzzy rule base, as well as their hybridisation with other methods of natural computing, such as genetic algorithms. Hybridisation can be carried out according to the island scheme, when different algorithms solve tasks in parallel and autonomously with the exchange of the best solutions after a certain time, or according to the master-student principle, when the main algorithm - the 'master' - passes the solution of typical subtasks to the 'student' - a specialised, fast algorithm.

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