Науковий вісник НЛТУ України
Scientific Bulletin of UNFU
https://doi.org/10.36930/40350212
Article received 19.02.2025
Article accepted 02.05.2025
UDC 004.[021+67+9]
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ISSN 1994-7836 (print)
ISSN 2519-2477 (online)

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FEATURES OF USING SWARM INTELLIGENCE ALGORITHMS FOR DRONE ROUTE OPTIMIZATION

This paper investigates the use of swarm algorithms for optimising delivery routes using Unmanned Vehicles (UVs) as an effective alternative to traditional algorithms. Classical path planning algorithms such as Dijkstra's algorithm, A* or APF (Artificial Potential Field) can struggle in real-world environments due to the ability to fall into local minima, or due to increased computational complexity in cases with multiple obstacles. To avoid these limitations, the research focuses on path-planning methods through swarm algorithms, many of which are inspired by animal biological behaviour. The article considers the features of operation and suitability for use in dynamic conditions of such algorithms as Particle Swarm Optimisation (PSO), Artificial Bee Colony (ABC), Cuckoo Search Algorithm (CSA) and Sparrow Search Algorithm (SSA). The study showed that there is no one universal algorithm for all types of environments. All algorithms demonstrate high performance when used under the best conditions. An algorithm's effectiveness depends on considering weaknesses and strengths when planning a task. It was found that PSO shows fast convergence even when using a large number of agents, which makes it suitable for route planning in swarm systems. Instead, the extensibility of the ABC algorithm and its ease of computational complexity allows for the efficient distribution of tasks among agents in large swarm systems. The CSA allows for the best local planning, which, in combination with other algorithms, allows for the best results in the balance between global and local route planning. SSA achieves fast convergence at the cost of computational resources, while ensuring execution in a dynamic environment. The results of the study show that the best algorithms for dynamic environments are those that combine local and global search capabilities, such as PSO modifications. The study emphasises the role of swarm intelligence algorithms in improving UAVs' performance by providing robust, efficient and scalable delivery routes. Future research could concentrate on exploring new hybrid algorithm models that combine swarm intelligence algorithms with machine learning technologies to improve algorithm outcomes in dynamic environments. In order to enhance the algorithms and analyse their limitations, further testing of the algorithms in complex environments with a large number of interferences is important to make further improvements to the algorithms.

Keywords: Particle Swarm Optimisation (PSO); Artificial Bee Colony (ABC); Cuckoo Search Algorithm (CSA); Sparrow Search Algorithm (SSA).

Introduction / Вступ

Since the beginning of the 21st century, the role of drones, also called UAVs (unmanned aerial vehicles), has increased significantly. Their use, both in crisis situations, such as military operations and in everyday life, for agriculture and delivery of various products in modern cities, has developed massively. The majority of tasks related to the delivery of goods or other types of cargo by drones are usually solved by the TSP (Travel Salesman Problem). For route planning, most algorithms that solve this problem can be divided into classical and swarm algorithms. The classical algorithms include the Dijkstra algorithm, which can be applied to drone control. However, the disadvantage of this algorithm is its high computational complexity and low efficiency due to the constant search for path nodes; instead, the A* or APF (Artificial potential field) algorithm can be used. The A* algorithm and its analogues, such as the Theta Algorithm and the Lazy Theta Algorithm, can be used to control drones in a 3D environment. However, this algorithm relies on heuristic grid values around the current way-

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Цитування за ДСТУ: Дебеляк Ю. П., Рабійчук І. О., Сердюк П. В., Фечан А. В. Особливості використання алгоритмів ройового інтелекту для оптимізації маршрутів дронів. Науковий вісник НЛТУ України. 2025, т. 35, № 2. С. 110–115.
Citation APA: Debeliak, Yu. P., Rabiichuk, I. O., Serdyuk, P. V., & Fechan, A. V. (2025). Features of using swarm intelligence algorithms for drone route optimization. *Scientific Bulletin of UNFU*, 35(2), 110–115. https://doi.org/10.36930/40350212

point, so it and its analogues are not able to solve problems when there are several optimal solutions. As for the APF algorithm, working with it has its limitations. Although it proves to be quite effective, it has such disadvantages as local minima and GNRON (Goal Non-Reachable with Obstacles Nearby, in the case of many obstacles, zones are formed where the force of attraction and repulsion are equal to each other, which causes the UAV to stay in one place), and work with dynamic obstacles. Instead, swarm algorithms can be used to solve TSPs. They can be used to optimise delivery routes both in logistics when modelling delivery routes and during delivery itself to effectively avoid obstacles encountered along the routes. The main advantage of swarm algorithms is their decentralisation, although standard versions were developed for static conditions, their modifications have better adaptability to work in dynamic conditions.

Object of research – the adaption of swarm algorithms to optimize the drone delivery route.

Subject of research – methods and means of determining drone delivery routes to the destination, which will allow for planning near-optimal safe routes.

The purpose *of the* research – determine the efficiency, advantages, and limitations of various swarm intelligence algorithms for UAV route optimisation, which will lead to increased stability and reducing computational time.

To achieve this *purpose*, the following main *research objectives are identified*:

- analyse the principles of operation of PSO, ABC, CSA, and SSA to reveal how they handle route planning in UAV systems
- investigate each algorithm's effectiveness in static and dynamic environments, which will enable identification of relevant strengths and weaknesses;
- investigate the possibility of improving the algorithm by modifying it, which will lead to increased stability and reducing computational time.

Analysis of recent research and publications. One of the main problems with using drones is their limited payload capacity. Therefore, the use of standard swarm algorithms has its specifics.

Authors in the article [3] analysed the use of the ant colony algorithm (ACO-DTSP) to optimise UAV swarm routes. The study tested the ACO-DTSP algorithm and its advantages over the Christofides, K-Opt, and Lin-Kernighan heuristic methods, showing significant improvements in time efficiency. The algorithm demonstrated a 20 % improvement in the task execution time relative to the entire search method for a small number of points. This algorithm also copes better with node load variability, making it better in real-world condition.

The paper [12] analysed swarm algorithms such as DQN-SISA and classical algorithms such as ACO, PSO, WOA, and GSO. A feature of the DQN-SISA algorithm is the combination of the Q-learning algorithm, which involves reinforcement learning, and classical swarm algorithms. Digital maps of the area with a size of 100 km × 100 km × 300 m were used to model the real field. As a result, DQN-SISA efficiently planned the route of drones, even in dynamic environments, and in various tests, surpassed all classical algorithms, demonstrating the prospect of combining deep machine learning algorithms with swarm algorithms. The field of application of unmanned aerial vehicles is vast, and one of the best areas of drone application is in places that are dangerous to human life and health.

The study [1] analysed the performance of swarm algorithms in hazardous waste collection using the MWMTT heuristic and its improved version IMWMTT to generate a set of routes. To measure the effectiveness of the algorithms, tests were conducted on a dataset that included parameters such as the weight of waste collected from each collection site, the maximal flight time of the UAV, and the battery recharge duration of the UAV. The combined approach showed the best results in minimising the delivery time, demonstrating an improvement in the objective function values of more than 30 %.

In paper [2], the authors introduced the Greedy Best (GB) and Dual Path (DP) algorithms. The GB algorithm maximizes coverage by expanding paths based on minimal costs, offering superior performance in coverage and execution time. The DP algorithm constructs forward-return paths concurrently, ensuring UAVs remain closer to the source during low battery levels. Both methods optimize routes dynamically without increasing computational complexity, making them suitable for real-time applications.

In paper [7], the use of swarm algorithms for environmental underwater monitoring was investigated since classical algorithms do not take into account the underwater environment, the Improved Artificial Jellyfish Search Algorithm was used. As a result of the experiments in a simulated environment with artificial ocean currents, the stability and efficiency of the swarm algorithm were shown, and its undeniable advantage over classical algorithms such as Dijkstra's algorithm and A* was demonstrated.

Algorithms of swarm intelligence demonstrate high adaptability in route planning for unmanned vehicles. Review [13], covers swarm algorithms such as particle swarm optimisation (PSO) and ant colony optimisation (ACO) due to their stability compared to traditional heuristic methods.

Recent studies have further advanced the efficiency of path planning using swarm intelligence algorithms. In the study [25] the authors introduce a PSO-based motion planning pipeline adapted for use in autonomous vehicles. The resulting algorithm provides modular, flexible and fast path planning, ensuring efficient trajectory planning in diverse scenarios. The robustness of the new algorithm has been validated using real-world simulation in everyday traffic conditions.

These studies reveal the diversity of swarm and hybrid algorithms for route planning, although they leave the need for a comprehensive analysis and comparison of various swarm intelligence algorithms in order to evaluate the optimality of each route planning algorithm's usage in different scenarios.

Materials and methods of research. In this study, several modern swarm intelligence algorithms were used to optimize the delivery routes of unmanned aerial vehicles (UAVs). The algorithms analysed included Particle Swarm Optimisation (PSO), Artificial Bee Colony (ABC), Cuckoo Search Algorithm (CSA) and Sparrow Search Algorithm (SSA), methods for evaluating efficiency of provided algorithms in path optimization task.

Research results and their discussion / Результати дослідження та їх обговорення

PSO (Particle Swarm Optimization) algorithm works by optimising initial solutions so-called particles, to find the best solution of the system, which is called global best [24]. Each particle adjusts its movement in space, considering global and personal best with random values, evaluating the newly obtained result, thus improving either the personal best result or the global best result. Algorithms rPSO (Ranking-based PSO) and apfrPSO can be applied to improve the performance. The rPSO works by modifying the particle's inertia, which leads to better solutions, improved searchability, and improved performance at the initial and final stages, by focusing on more promising particles [26]. Algorithm apfrPSO uses the principle of potential fields where certain fields repel, and others attract the drone. However, this method can give negative results in the case of local minima, when the repulsive and attractive forces are equal to each other. The use of PSO in UVs gives better results than standard algorithms such as DAFSA (an algorithm based on the Dijkstra algorithm) [24] and D* Lite [26] when tested in simulated environments. The algorithm also proves to be extremely effective when operating multiple drones, with 20 drones saving more than 5 times the memory. When performing a search task, the use of this algorithm becomes appropriate only when using a more significant number of drones, since for 4 drones, it is more efficient to use standard search algorithms. One of the advantages of the algorithm is its speed: if GA (Genetic Algorithm) requires 50-100 iterations to achieve the optimal result, PSO allows to achieve the same in 20-40 iterations and also reduces the route planning time by up to 20 % compared to traditional ACO. However, like similar algorithms, PSO is sensitive to initial parameters and tends to converge prematurely, especially in large and complex environments. The algorithm also proves unreliable in dynamic environments, in conditions of constant route re-planning, increasing the number of collisions [15].

ABC (Artificial bee colony) – models the social hierarchy of a bee colony. In a colony, bees are divided into three groups: workers, observers and scouts. Each worker bee is assigned to a single food source, indicating a possible solution. Thus, the number of bees is equal to the number of simultaneous possible solutions. Initially, food sources are randomly distributed, and then worker bees optimise solutions by choosing random partners so that the new solution is different from the previous one. At each iteration, the new sources are evaluated using an objective function. Observer bees choose sources based on the probability, which is calculated as the ratio of the value of the food source to the total sum of the values of all solutions. If, when trying to improve a solution, the bee cannot change it within a certain set number of iterations, the food source becomes abandoned and the bee becomes a scout to explore new solutions [9]. In the tests, the algorithm proves to be slightly faster than PSO, significantly increasing the difference in results when using multiple UAVs. To organise a flight of 6 UAVs, ABC requires 80 seconds of working time, while PSO requires 112 seconds, but when using a single UAV, the difference is minimal, which can be explained by an error in the PSO parameter setting [17]. The algorithm requires information about the positions of all UAVs to work effectively, which may limit its use in conditions of limited communication, also algorithm's performance in dynamic conditions could be improved. One of the peculiarities of the algorithm is its inability to remember the previous best solutions, which does not allow it to use historical data for further optimisation. For similar conditions, ABC optimises up to 0.123 kilometres of the route, while PSO shows 0.167. The algorithm also allows for quick, close-to-optimal solution finding, which is needed when computing power is limited. The algorithm shows itself to be slower in stabilising the optimal path. In the case of similar conditions, ABC stabilised in 10 iterations, while PSO stabilised in only 3 [4].

CSA (Cuckoo Search Algorithm) inspired by the behavior of cuckoo birds. Cuckoos lay their eggs in the nests of other species to breed, and if the owner of the nest discovers that the egg is not their own, the eggs are either rejected or the host bird leaves the nest. This process is modelled by using Levy flights, a random process with steps distributed according to a stable Levy distribution. The algorithm uses the principle that each cuckoo lays one egg in a randomly selected nest. The best nests, with the best eggs (solutions), are used to improve further results of the algorithm. The nests can recognise and eject other people's eggs with a certain probability, thus creating new nests in different locations. Levy flights generate new solutions that replace the old ones in a randomised improvement of the results. Due to the dynamic replacement of nests, the process is repeated and allows you to choose the globally best solution [6]. Algorithm is effective in local search and takes 20 % less CPU time than PSO [5]. Also, CSA requires few parameters changes to adapt to different conditions, which makes it fast to set up. Combining this algorithm with PSO allows CSA to achieve an improvement in global search while maintaining the advantage of CSA's local search. The standard CSA algorithm uses a random nest-leaving method, leading to the accidental loss of the results. Using tournament to determine the worst and best nests, could improve the local search capability of the algorithm and prevent it from falling into local minima [19]. Another optimisation option involves reducing the random factor of Lévy flight, by introduction of a step control. This modification controls the search depth, achieving faster convergence compared to the standard algorithm and improving the algorithm in the later stages of the search. Such an algorithm allows for the smooth acceleration and deceleration of UAV, simulating behaviour close to the real world [21].

SSA (Sparrow Search Algorithm) is inspired by the behaviour of flocks of sparrows, which have two roles: producers and scroungers. The task of the producers is to find food sources (possible solutions), while avoiding danger by changing their trajectory when a threat is detected. This behaviour improves local minimum avoidance. Scroungers, on the other hand, follow the producers and help to improve the solutions already found, without actively searching for new solutions. When the algorithm works, each position of the sparrow is a potential solution that can be improved in further iterations. By balancing the number of producers and scroungers, local and global searches can be adjusted [23]. The standard algorithm may have some problems with converging to the optimal solution due to the random behaviour of the algorithm [22]. Also, the complexity of parameter settings can lead to incorrect algorithm application, reducing its effectiveness. Using this algorithm in UAVs can significantly improve performance and reduce flight planning time compared to PSO, planning efficient and safe routes in 3D environments [8]. Modification of SSA with chaotic distribution of the population in the initial stages, improved adaptive inertia weight, and the use of Cauchy-Gaussian mutation to overcome local stagnation allows to improve the results of the standard algorithm by 15-20 %, showing the best performance in path length optimization.

However, it shows 50 % longer computation time compared to PSO and 36 % longer than ABC [10].

Each algorithm analyzed has its strengths and drawbacks, that affect the efficiency of its usage across different environments. To identify the most suitable algorithm for a specific task, their performance was evaluated based on 9 key criteria in value from 1 to 10. The following diagram illustrate the performance of algorithms in each criterion. Figure demonstrates a comparative performance of these algorithms across nine key criteria, including convergence speed, computational complexity, scalability, and suitability for 3D path planning. The figure was made using research findings from multiple scientific sources, namely [4, 6, 9, 11, 16, 18, 19, 22, 24, 25].

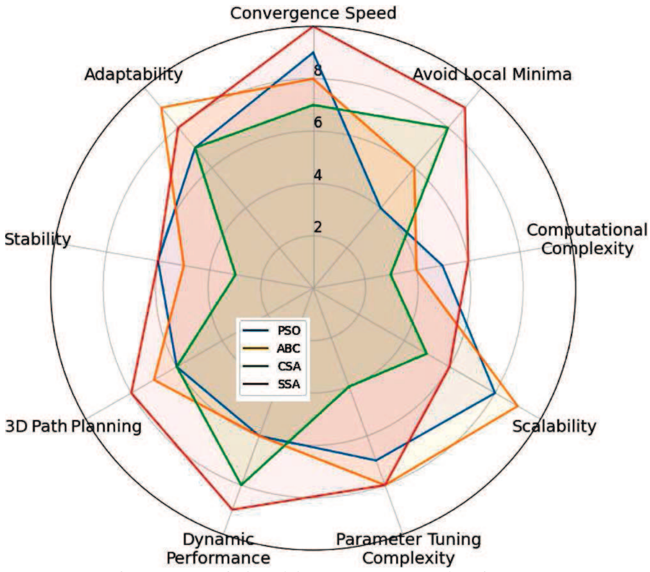

Figure. Performance of algorithms across metrics / Продуктивність алгоритмів за метриками [25]

Particle Swarm Optimization (PSO) has a fast convergence rate, but is also capable of premature convergence, which affects the efficiency of the algorithm's results, especially in complex environments. The need to configure many parameters, this feature allows you to fine-tune the algorithm to perform a specific task, while increasing the complexity of the application. Its use in 3D environments is difficult, and the algorithm becomes less efficient, especially when there are a large number of obstacles.

Artificial Bee Colony (ABC) allows for efficient convergence, especially in the presence of multiple UAVs, outperforming PSO in that case. Due to the lack of the ability to obtain previous best positions, the algorithm has difficulty avoiding local minima, which makes it less effective in dynamic environments. The algorithm scales well to multiple agents, but its tuning can be challenging. The stability of the ABC is slower than PSO because of slower stabilization speed. Due to its adaptability, the algorithm can be effectively applied to swarm systems.

Cuckoo Search Algorithm (CSA) shows efficient convergence, especially in local search. CSA has a good ability to avoid local minima, especially if it is integrated with other algorithms. Its fairly average computational complexity and small number of parameters makes it a balanced choice between simplicity and computational complexity.

Sparrow Search Algorithm (SSA) has high convergence speed and, a high ability to avoid local minima in cost of higher computation complexity, which makes its scalability more difficult, compared to more traditional swarm algorithms. Also, tuning its parameters to show the best performance in the specific scenario can create a challenge for its fast set-up. SSA allows for application in dynamic environments and 3D environments, generating efficient and safe routes. For better understanding weak and strong sides of each algorithm each metric was displayed in table (Table).

Table. Comparison of the performance of PSO, ABC, CSA and SSA algorithms / Порівняння ефективності роботи алгоритмів PSO, ABC, CSA та SSA

Metric	PSO	ABC	CSA	SSA
Convergence Speed	High	High	Medium	High
Avoid Local Minima	Low	Medium	High	High
Computational Complexity	Medium	Low	Low	Medium
Scalability	High	High	Low	Medium
Parameter Tuning Complexity	Medium	High	Low	High
Dynamic Performance	Medium	Medium	High	High
3D Path Planning	Medium	Medium	Medium	High
Stability	Medium	Medium	Low	Medium
Adaptability	Medium	High	Medium	High

As a result, the use of PSO, ABC and SSA is the most versatile choice for UAV systems. PSO is more effective in large, static environments, where ABC allows for the use and coordination of a multi-drone system. SSA, on the other hand, allows for rapid re-routing in response to threats, making it effective in dynamic environments.

Discussion of research results. The results obtained can be compared with studies that focus on the effectiveness of various algorithms in the route planning task, for example, in work [20] analysed the PSO, FA, ACO algorithms with other algorithms. As a result, the capabilities of the algorithms were determined. The advantage of local planning algorithms, such as PSO, FA, ACO and others, compared to the global approach, was noted due to the ability to dynamically respond to changes in the environment and reduce computational complexity. Still, the combination of such approaches allows one to achieve the best results.

In the study [16], the authors compared swarm algorithms with each other to solve the Travel Salesman problem. As a result of the research, the best swarm algorithm for solving this type of problem was ABC. It is worth noting that the comparison was carried out in a two-dimensional environment and without modifications that could improve the efficiency of the algorithms.

Researchers in the paper [14], studying the use of swarm intelligence algorithms and its application to planning the routes of flocks of unmanned vehicles, note that the biggest trends in the modern development of swarm algorithms are their combination with reinforce learning and evolutionary computation methods. RL provides flexibility in dynamic environments, while EC allows for improved optimization in complex environments. The authors believe that one of the problems of research on swarm intelligence is its non-standardized results and lack of testing in real-world conditions.

The results of the study can be compared with the results of the study conducted in the paper [18], which investigated the ACO, PSO, ABC, FA and Bat algorithms when used to intercept targets in 3D space. As a result of the study, the authors noted the advantages and disadvantages of each of the swarm algorithms and noted the prospect of creating new, hybrid algorithms that combine the advantages of several algorithms.

In work [11], a hybrid PSO-based PPSwarm algorithm is proposed for cooperative path planning of a large number of drones. Standard metaheuristics (differential evolution – DE, classical PSO, ABC, grey wolf optimisation – GWO, and adjusted PSO (SPSO)) were compared with the developed hybrid. The authors note that with a large number of agents, the standard PSO and even the improved SPSO show premature convergence. The ABC algorithm proved to be more robust to local minima, but too dependent on the initial route. But the combination of ABC and PSO (as in PPSwarm) significantly improves the plan's efficiency.

So, based on the results of the work performed, it is possible to formulate the following scientific novelty and practical significance of the research results.

Scientific novelty of the obtained research results – for the first time, a comprehensive analysis of the swarm intelligence algorithms PSO, ABC, CSA and SSA was done, researching their basic principles of operation, which made it possible to investigate their strength and weaknesses, to formulate criteria for choosing algorithm, depending on their capabilities in different environments.

Practical significance of the research results – the results of the study can be used to develop adaptive systems for automated route planning, which allows for increased efficiency of their application in different environments, multiple obstacles and scenarios with limited computing resources.

Conclusions / Висновки

The study achieved the goal of determining the effectiveness, advantages and limitations of swarm intelligence algorithms. The following key results were obtained based on performed analysis of the principles PSO, ABC, CSA, and SSA algorithms, the study of their effectiveness in different environments, and research of possible modification possibilities. Based on the results of the research the following main conclusions can be drawn.

1. The research found that each algorithm has its unique strength and usability field because of the specific biological behaviour of the species it is based on. For example, PSO demonstrates fast convergence due to global and local search algorithms, while CSA allows for avoiding local minima by using Lévy flights distribution. ABC, which is based on the hierarchal organization of bees in the colony, provides scalability when used in a system with multiple UVs. SSA stands out for its ability to provide dynamic responses to appearing threats. These characteristics make each algorithm suitable for specific scenarios, demonstrating the lack of one universal solution.
2. Investigation of performance in dynamic and static environments has shown that PSO and ABC are optimal for static environments where the convergence speed of PSO and task allocation of ABC are important. However, CSA and SSA when used in dynamic environments outperform PSO and ABC, proving to be more robust due to the possibility of local search of SSA and threat adaptation of SSA. For example, modified SSA improved the result path by 15-20 %, although using more computational power for calculation than PSO. This indicates that a meticulous analysis of the intended usage environment must be conducted in order to achieve a balance between speed, accuracy, and resource consumption.
3. The paper analysed the possibility of algorithms' modifications. Modifications prove to compensate for shortcomings and leverage each algorithm's strengths. For example combination of PSO global search with CSA local search reduced route planning time in complex environments tests. In addition, the possibility of machine learning-based modifications provides improved adaptation to dynamic conditions.
4. Future research could concentrate on developing further algorithms hybrids, improving efficiency and adaptation capabilities while planning routes in dynamic environments. Also, testing algorithms in real-life conditions with factors such as communication limitations, weather changes and other unpredictable variables, could reveal aspects that affect practical applications.

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ОСОБЛИВОСТІ ВИКОРИСТАННЯ АЛГОРИТМІВ РОЙОВОГО ІНТЕЛЕКТУ ДЛЯ ОПТИМІЗАЦІЇ МАРШРУТІВ ДРОНІВ

Досліджено особливості використання алгоритмів ройового інтелекту для оптимізації маршрутів доставки безпілотними апаратами корисного навантаження. Класичні алгоритми планування маршрутів, такі як алгоритм Дейкстри, A* або APF, мають недоліки під час використання в умовах реального світу, через можливість впадання у локальні мінімуми та підвищену обчислювальну складність за багатьох перешкод. Щоб обійти ці недоліки, запропоновано використання алгоритмів ройового інтелекту для планування маршрутів, багато з яких натхненні біологічною поведінкою тварин. Розглянуто особливості роботи та придатність використання у динамічних умовах таких алгоритмів, як Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Cuckoo Search Algorithm (CSA) and Sparrow Search Algorithm (SSA). За результатами дослідження з'ясовано, що не існує єдиного універсального алгоритму для всіх типів середовищ. Усі алгоритми показують високу ефективність у разі використання у найкращих для них умовах. Встановлено, що PSO має швидку збіжність навіть у разі використання великої кількості агентів, що робить його придатним для планування маршруту у ройових системах. Натомість розширювальна здатність алгоритму ABC та його легкість в обчислювальній складності дає змогу виконувати ефективний розподіл завдань між агентами у великих ройових системах. Алгоритм CSA дає можливість досягти найкращого локального планування, що у комбінації з іншими алгоритмом сприяє досягненню найкращих результатів у балансі між глобальним і локальним плануванням маршруту. Алгоритм SSA досягає швидкої збіжності в разі використання більших обчислювальних ресурсів, водночас забезпечуючи виконання планування у динамічному середовищі. За результатами дослідження визначено роль алгоритмів ройового інтелекту у покращенні продуктивності БПЛА, водночас забезпечуючи надійні, ефективні та масштабовані маршрути доставки. Майбутні дослідження можна спрямувати на вивчення нових гібридних алгоритмічних моделей, що будуть поєднувати алгоритми ройового інтелекту з технологіями машинного навчання для покращення їхньої ефективності в динамічних середовищах. Для покращення роботи алгоритмів та тестування їх обмежень важливе тестування алгоритмів в умовах комплексних середовищ з багатьма перешкодами.

Ключові слова: оптимізація рою частинок (PSO); штучна бджолина колонія (ABC); алгоритм пошуку зозулі (CSA); алгоритм пошуку горобця (SSA).