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Safety and Surveillance on Unmanned Aerial Vehicles Control Systems and Optimization Methods: A Systematic Review

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ABSTRACT

Unmanned Aerial Vehicles (UAVs) have become an issue of high research activity because of their extensive variety of applications in agriculture, logistics, security, and emergency responses. Though they are advancing at a very fast rate, their operational capability is still limited due to a number of issues, the primary ones being short flight range, inadequate autonomy, and the difficulty of collaborating with UAVs. The short battery life, which has been a source of energy constraint, has led to the investigation of hybrid propulsion systems, improved energy management, and automated battery replacement via docking systems. No less important are the questions of autonomous navigation, supposed to be based on efficient path planning, collision avoidance, and optimization of the payload. The coordination of swarms of UAVs also adds complexity to the system, which, in turn, necessitates providing the system with dependable communication and safety measures. Recent research indicates that the application of artificial intelligence and optimization solutions, including Reinforcement Learning (RL) and Deep Q-Learning (DQL), can be used as a path-planning and coordination tool, but not in very dynamic or unpredictable environments. As UAVs transition from a hobby tool to an indispensable part of disaster management and precision agriculture, there is a growing need to overcome these obstacles. This systematic review investigates the current innovations within the area of UAV control and optimization, as well as the current constraints and future research opportunities to attain trustworthy, self-governing and power-efficient UAV systems.

1. Introduction

Unmanned Aerial Vehicle (UAV) technologies represent modern cutting-edge technologies that affect huge industries spanning from logistics to agriculture and environmental monitoring [1], and disaster relief [2]. The UAV systems are developing into vital operational tools which enable the replacement of human operators in manual tasks, particularly in hostile circumstances and unreachable locations and quick response situations [3]. UAVs provide multiple application opportunities such as precision farming for harvesting, monitoring and disaster relief monitoring for airspace observation [4]. The technology innovations that remain unknown in the realm of UAV systems enable the incorporation of Machine Learning (ML) [5], Artificial Intelligence (AI) [6], and analytics-oriented solutions [7], with the idea offering the UAVs the opportunity to autonomously act and make critical in-flight decisions [8]. This ability helped the UAVs to undertake difficult tasks like determining the threats and risks of the environment and preventing collisions, among others [9]. The evolution of UAVs increased their functionality, and the circumstances rendered them important to serve all the business-associated tasks, commencing with the environmental examination, progressing to the study of rescue missions [10]. These advanced optimization needs of the UAV development performance are independent of their established abilities. Good analysis techniques and advanced algorithms are required to provide reliability, safety, and efficiency of the UAV systems [11]. In this case, AI solutions based on optimization are implemented [12]. Predictive analysis is conducted by the AI to adjust in the behavior of the UAVs when they are in operation, which can enhance their operating efficiency and safety [13]. The systematic review analyses how reinforcement control of UAV systems benefits from machine learning, together with solution algorithms, when used as inputs for performance improvement and enhanced safety alongside reliability during operations. It is envisioned to take the concept of safety mechanisms of UAV beyond current limits using AI and analytics to pre-calculate the probability of failure beforehand and pave the way toward more automated and smart UAV systems [14], [15]. Fig. 1 and Fig. 2 are the topologies of public and safety as shown.

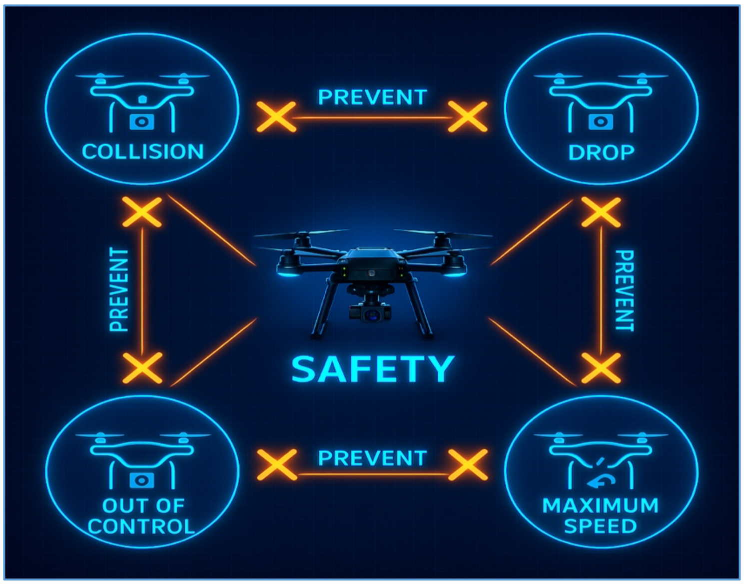

Fig. 1. UAV safety structure

The Unmanned Aerial Vehicles have evolved far beyond their initial recreational application and currently find application in wide areas, including precision agriculture [16], environmental surveillance [17], disaster response [18], and logistics [19]. This increases the opportunities tremendously, and at the same time, it exposes deficiencies of airborne range, stability of navigation, and performance in the case of multiple UAVs [20]. To overcome such concerns, scholars are turning more to optimization strategies underpinned by the AI and the ML [21]. Some examples are reinforcement learning and swarm-based path planning, predictive models and heuristic algorithms of energy management and fault detection [22]. These methods, when applied together, enhance autonomy and safety and enable the UAVs to adapt more to the uncertain or dynamic conditions. In spite of these developments, there has been difficulty in scaling such solutions to real-world applications, especially with the limitations of onboard computation and the requirement of real-time responsiveness. Making the transition between theory and practice, therefore, remains one of the central areas of research on UAVs [23].

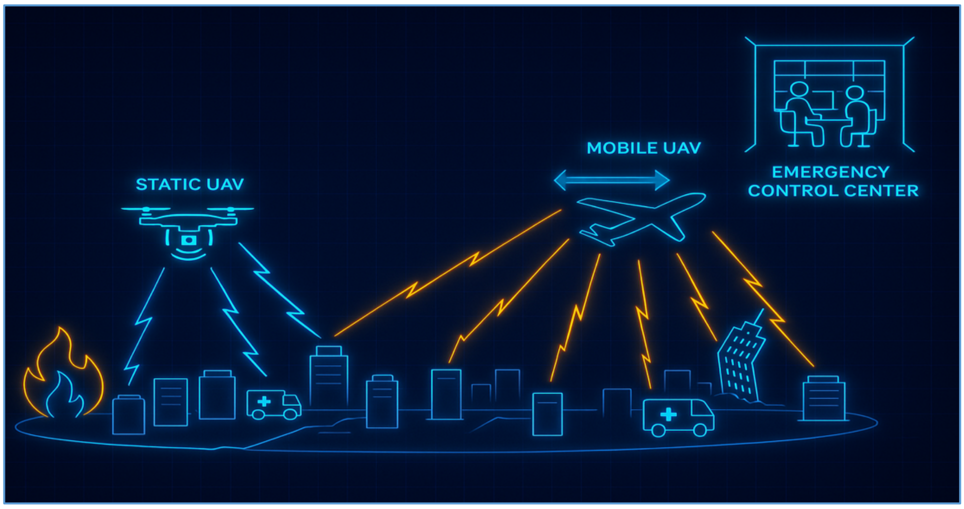

Fig. 2. UAV public safety topology

The paper explores the evolution of UAV control systems by reviewing the recent studies on the implementation of optimization techniques, data-driven solutions, and machine learning. The review will assess the advances in methodology, such as predictive models, regression, and classification algorithms, to determine which of them have the highest potential to enhance UAVs. They are applied to various industries with a special focus on the way in which computational techniques help maintain the reliability of operations, improve safety systems, and provide opportunities to detect failures of the system at the earliest. The information was based on various sources that were relevant and evaluated in terms of their relevance to UAV technologies. The paper will describe the previous real-life applications of optimization and ML algorithms, after which it will discuss some of the main problems found in the literature and the criteria applied to assess the success of an algorithm. Performance assessment involves a comparison of reported measures of accuracy and transparency. Besides, the paper discusses the obstacles to implementation by emphasizing the usability of the data, computational constraints, and real-time decision-making requirements. These findings are used to give recommendations on how to come up with more efficient algorithmic solutions and better data-processing strategies. The rest of the paper is organized with the following structure: Section 2 contains the description of the research methodology, Section 3 contains the description and discussion of the results, and finally, Section 4 provides the conclusion of the paper with recommendations on how to develop the UAV system performance and safety further.

2. Methods

This paper is based on the systematic review methodology, implemented by following the guidance of Preferred Reporting Items of Systematic Reviews and Meta-Analyses (PRISMA) [36-6] to examine the uses of machine learning and optimization algorithms in UAV technologies. Four large academic databases, which include IEEE Xplore, Web of Science (WoS), ScienceDirect (SD) and Scopus, were searched with the help of properly chosen keywords connected to the UAV applications, machine learning methods and optimization approaches. These databases have been selected due to their wide-ranging scope of engineering, computer science, and UAV research, where IEEE Xplore offers the latest trends in electronics and control systems, and WoS and Scopus provide an interdisciplinary view, and SD can provide in-depth engineering knowledge. The search was followed by inclusion criteria to make sure that the information is relevant, has sound methodology and quality of the study. To counter the eventuality of bias, we also captured other criteria such as publication venue, clear evaluation design, and report results transparency. The focus of data mining was based on the chief areas, which included the algorithms employed, assessment techniques and the degree of accuracy that was reported. The rigor of methodology of each of the selected studies was then assessed, and the limitations that might have been encountered were also assessed. In the results section, we provide the comparative discussion of the performance of the algorithm in various conditions of UAV application, upcoming trends, existing literature additions and gaps. Accordingly, the systematic review provides the general picture of the computational approaches applied to support the development of UAVs and critically examine their reliability and usability as illustrated in Fig. 3.

Fig. 3. Search strategy method

The systematic research of the literature presents the limitation of the scope of analysis to examine the evolution of the UAV control systems to address the primary issues of safety and optimization. Recent news suggests that there is a growing use of sophisticated algorithms to improve fault detection, collision avoidance, path planning and energy management. In the meantime, the idea of optimization plan has become vital to the enhancement of endurance and coordination of multi-UAV tasks. The review explains through these themes not only the summarization of the current developments, but also the creation of the fact that gaps remain and have been the obstacle to the implementation of UAVs in real life and in complex environments.

2.1. Search Strategy

Four large databases, i.e. IEEE Xplore, Web of Science (WoS), ScienceDirect (SD) and Scopus were searched systematically to find references related to the English language that were published between 2015 and 31 March 2025. These databases were selected as they provide a broad scope of research in the field of UAV technology, ML and optimization algorithms which are all central to the impetus of our research. Such databases prove extremely useful in the context of collecting the latest and most relevant research due to the swift development of UAV systems and their extended use in different industries. Three Boolean search strategies were used to reduce the search with a combination of several varying keywords of the ubiquitous term of unmanned aerial vehicle and its variations e.g. unmanned aerial vehicles OR UAV. The search parameters that we set were concerned with the research procedures that connect AI and ML algorithms to UAV systems along with optimization and safety control approaches. The research methods enabled the discovery of relevant studies that examine how to boost UAV performance and minimize risks, and how to best optimize systems with advanced algorithmic approaches. Our specialized search approach enabled us to acquire diverse studies demonstrating the state of UAV technology regarding machine learning methods, as well as optimization strategies and safe applications. Our method helped identify major research fields and entirely understand the ways UAV systems utilize cutting-edge technologies.

2.2. Inclusion Criteria

The author must establish the research goals and limitations before presenting the inclusion requirements. The research evaluates current practices of new technology fusion, including artificial intelligence, together with machine learning and optimisation algorithms in unmanned aerial vehicles. The research evaluates diverse articles to discover innovative approaches and methods which boost UAV capabilities, particularly in safety parameters and control aspects, together with optimisation strategies and performance improvement measures. These criteria determine the selection procedure for articles used in this research by describing how to implement them:

- Articles utilised for this study are journal articles and conference articles in English that report on various years between 2015 and 2025.
- The study revolves around the collaboration of ML, AI, and optimisation algorithms in the design and optimisation of UAV systems. It is based on novel applications, methods, and strategies related to UAV control, safety, performance, and optimisation.
- The primary areas of development covered under the articles are adaptive control systems for UAVs, trajectory planning, collision avoidance, and classification tasks to increase decision-making capability of the UAV in dynamic environments. Fig. 4 illustrates the pie chart representing the spread of articles on the four major databases: ScienceDirect (SD), IEEE Xplore, Web of Science (WoS), and Scopus.

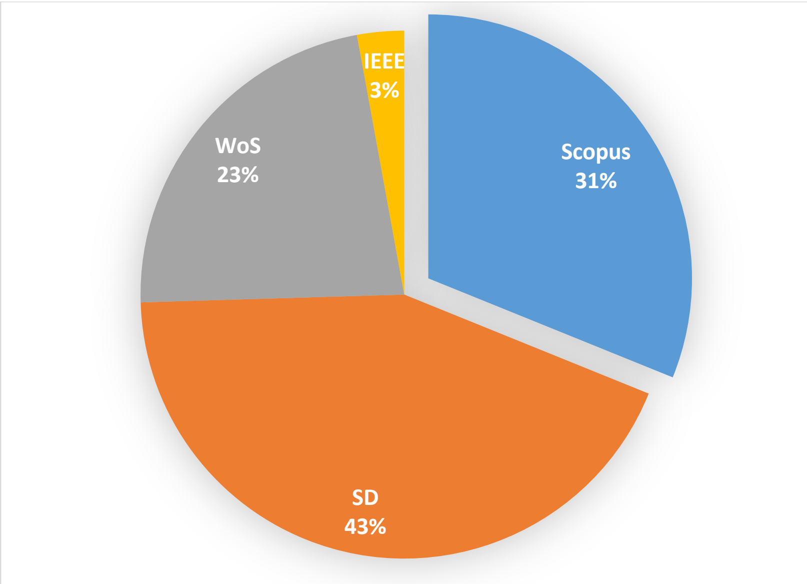

Fig. 4. Pie-chart for major databases

The research utilized the Boolean search sequences depicted in Table 1, which yielded the mentioned results. The research displays three separate UAV-focused search inquiries about safety algorithms, together with fault detection and optimization techniques. The data presented in the mentioned table displays the initial article counts from ScienceDirect, IEEE Xplore, Web of Science, and Scopus databases, which then leads to the final deduplicated article counts. The collected results cover numerous articles that discuss UAV control systems and optimization techniques.

2.3. Study Selection

To generate a list of quality and relevant articles, the systematic screening was applied in this paper. The initial step eliminated the duplicate articles, and the remaining articles were assessed according to the abstract and title. The screening procedure enabled us to locate the articles that are pertinent to conducting research pertaining to the UAVs and machine learning methods and algorithms. When the first screening procedure was finished, the research data and the definition of the review article were defined by systematic reading. The senior author, who is also the corresponding author, conducted strict check-ups on the entire research process including collection of data and analysis. This technique made the research meet the universal standards of research reliability and validity.

Table 1. Boolean search query in three different sequences

Seq.	Query Details Terms	Result of Databases	Final Results
1st query	("unmanned aerial vehicle" OR "unmanned aerial vehicles" OR "UAV") AND ("safety" OR "safety algorithms" OR "safety control") AND ("optimisation algorithms" OR "AI" OR "ML")	SD = 317 IEEE = 12 WOS = 193 Scopus = 248	780−11 (duplicates) = 769 Article(s)
2nd query	("unmanned aerial vehicle" OR "UAV") AND ("safety mechanisms" OR "fault detection" OR "collision avoidance") AND ("machine learning" OR "reinforcement learning (RL))"	SD = 181 IEEE = 9 WOS = 91 Scopus = 135	419−10 (duplicates) = 409 Article(s)
3rd query	("unmanned aerial vehicle" OR "UAV") AND ("path planning" OR "flight safety") AND ("optimisation techniques" OR "safety-based algorithms")	SD = 144 IEEE = 21 WOS = 39 Scopus = 77	281−5 (duplicates) = 276 Article(s)
Results for all queries			**1454 Articles**

2.4. Data Extraction and Classification

This systematic review aims at the analysis of the performance variance of ML, as well as optimisation algorithms when they are applied to improve UAV control mechanisms and navigation systems and safety capabilities. The analysis will involve the extraction and classification of appropriate studies regarding AI systems that will complement unmanned aerial vehicles [9]. In the review, the authors pay attention to the application of various ML methods to the problem of UAV control optimization since UAV technology involves various fields [24]. The research takes into account numerous facts obtained within the literature such as nationalities of the authors, year of publication, the number of articles published each year, and the number of articles in the database. This is to obtain an overall view of UAV research developments and trends. Moreover, the review touches upon the global extension of the use of UAVs, particularly of AI, employing different data mining and machine learning methods such as classification, regression, and prediction [25]. The study also extracted primary feature names, assessment processes, and accuracy metrics from the literature to provide a comprehensive analysis of UAV system performance and optimisation techniques [26]. In response to concerns from the public regarding UAV control and safety, the review formulates standard challenges, constraints, and suggestions based on the reviewed studies. The following Fig. 5 identifies the Word-Arts for AI methods that were employed in Unmanned systems.

2.5. Results

A search in several individual queries was performed in the IEEE Xplore, WoS, SD, and Scopus databases, giving a total of 1,454 records. After the elimination of 26 duplicates, 1,428 unique articles were left and filtered by the title and abstract using specific inclusion and exclusion criteria. This preliminary filtering was necessary to ensure that only papers that directly dealt with UAV control systems, safety measures or optimization measures were retained. Out of the process, 180 full-text studies were chosen to be further evaluated on eligibility. Having thoroughly analyzed the articles according to methodological consistency, the clarity of using the algorithm, and its relevance to UAV technologies, 170 were selected, and 10 articles were left that addressed all the requirements set. These last experiments were added to the qualitative synthesis and were the basis of the analysis of algorithm performance and research gaps performed afterwards. The general process of the selection, which involves identification, screening, eligibility evaluation, and inclusion, is presented in Fig. 6, which represents the stringent and transparent nature of the process that was implemented to guarantee the reliability and validity of this systematic review.

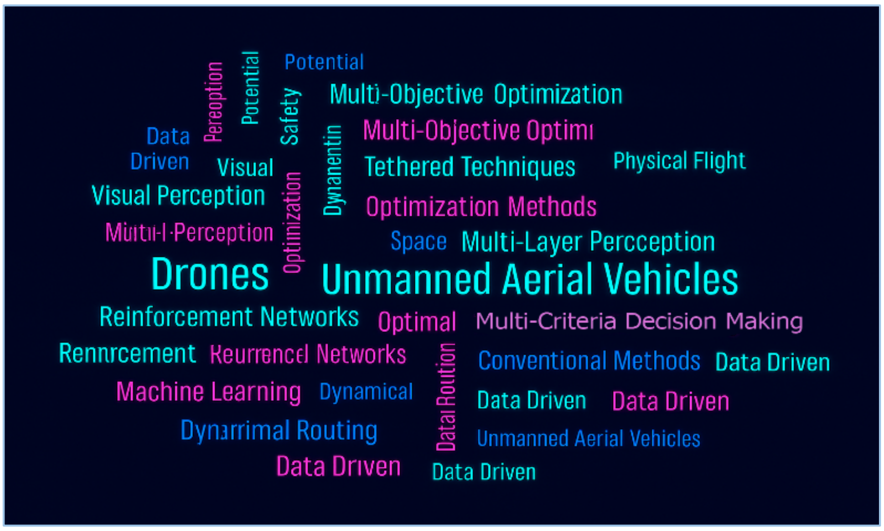

Fig. 5. Word-Arts for unmanned and AI methods

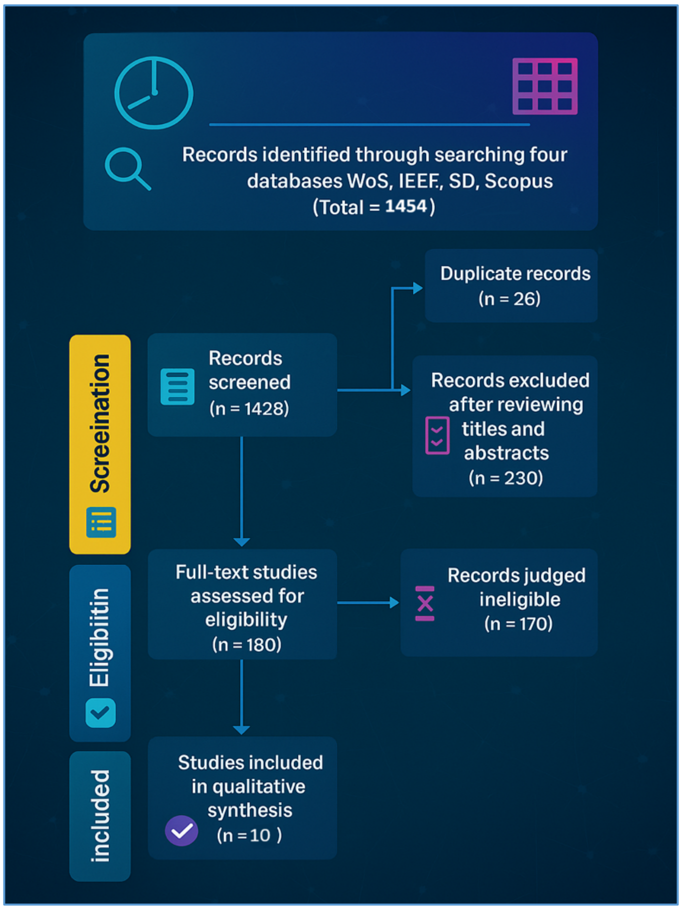

Fig. 6. Schematical approach for identification, screening and involve newest studies

2.6. Distribution Results

The review of the chosen articles demonstrated the obvious trends in the distribution of algorithms and media sources. The Nonlinear Model Predictive Control (NMPC) algorithm was the most common one and was found to be utilized in four studies, whereas the other methods, like Task Allocation, the Cuckoo Optimization Algorithm and the Naive algorithm, were mentioned one time each. Among the sources of publication, the Journal of Computer and System Sciences had the highest number of seven articles, followed by Ocean Engineering with two articles. The rest of the contributions were scattered across a number of journals, such as Propulsion and Power Research, Journal of Sound and Vibration, and Results in Physics, each of which was presented by one of the studies. These results, as Fig. 7 (in the form of a Sankey diagram of connections between algorithms, journals, and techniques), reveal not only the variety of methodological approaches to the problem of UAVs but also the fact that publications are concentrated in a few major journals.

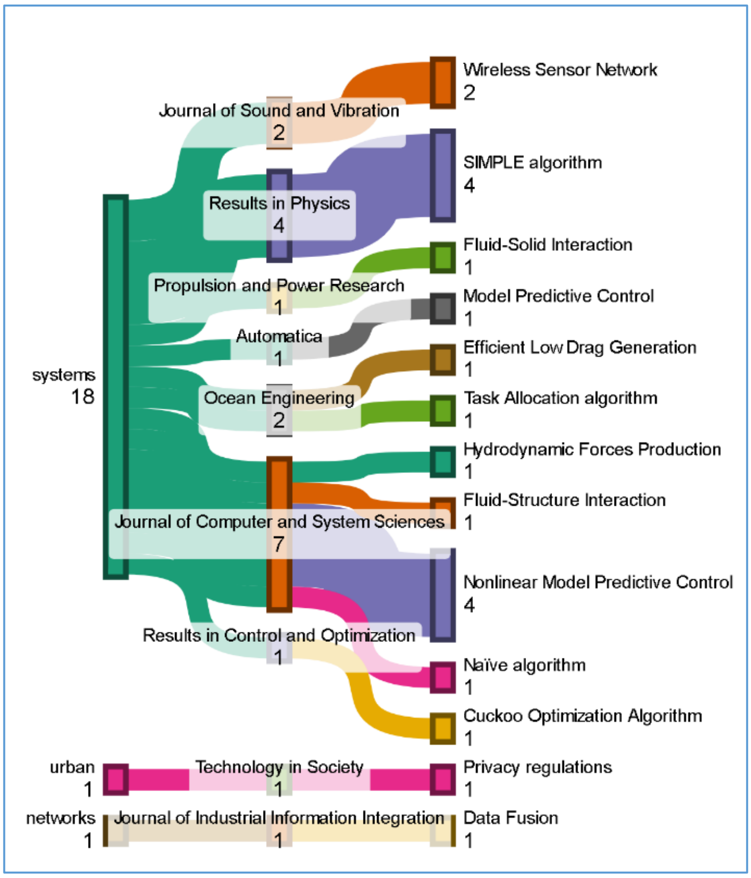

Fig. 7. Algorithms and techniques in Sankey Diagram against application nature and journals

The chronological distribution of the publications shows a strong tendency for the research activity to concentrate in recent years. The year 2021 was the most productive one as it registered four articles, and the years 2022 and 2023 came after with three articles respectively. No possible studies were found before this date, which suggests that the current combination of machine learning and optimization techniques into UAV systems has been a growing momentum in the past few years. This trend is represented in Fig. 8, which generalizes the distribution of the chosen studies annually. They are complemented by detailed information that is given in Table 2 on advanced UAV systems using these algorithms and Table 3 on the dataset and its sources. Collectively, these findings point to the rising research interest in the optimization of UAVs and the comparative recency with which the systematic application to this area occurred.

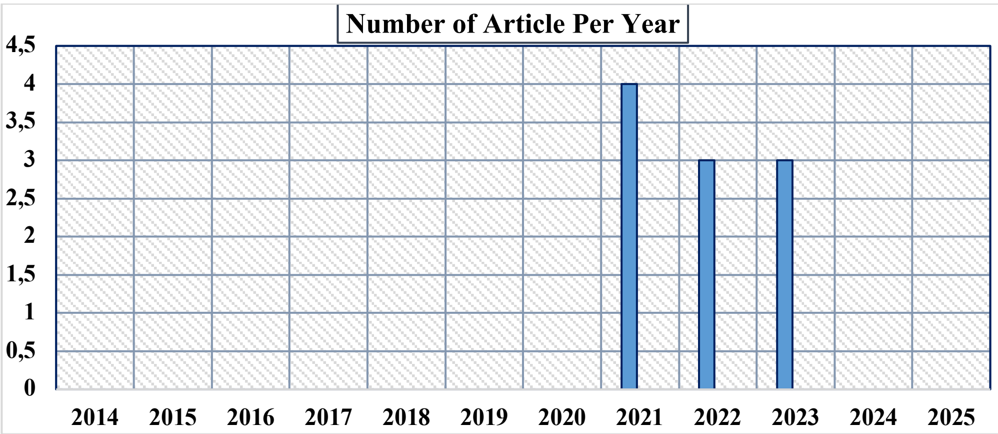

Fig. 8. Techniques and algorithms Synopsis was applied in the literature

Table 2. Unmanned systems safety with AI methods: State-of-the-art

Ref.	System Nature	AI Methods	Evaluations	Accuracy
[13]	UAV Path Planning	Reinforcement Learning (RL)	Simulation of optimal path planning for UAVs	90%
[14]	UAV Collision Avoidance	Deep Q-Learning (DQL)	Evaluating real-world collision avoidance	85%
[15]	UAV Swarming & Coordination	Particle Swarm Optimization (PSO)	Simulation of multi-UAV coordination and task assignment	92%
[16]	UAV Fault Detection	Support Vector Machine (SVM)	Evaluation of fault detection accuracy in real-time UAV systems	87%
[17]	UAV Optimal Design	Genetic Algorithm (GA)	Performance evaluation of UAV design parameters through simulations	93%
[18]	UAV Flight Safety	Neural Networks (NN)	Real-time flight safety risk prediction	88%
[19]	UAV Control System	Model Predictive Control (MPC), Linear Quadratic Regulator (LQR)	Evaluation through simulated flight tests and control stability	91%
[20]	UAV Energy Efficiency	Simulated Annealing	Optimization of UAV battery management for extended flight times	89%
[21]	UAV Navigation System	Artificial Bee Colony (ABC) Algorithm	Navigation accuracy and efficiency in unknown environments	90%
[22]	UAV Path Planning in Unknown Environments	Reinforcement Learning (RL)	Evaluation of path planning in dynamic environments	95%

3. Discussion

Research gap identification in UAV systems is a sequential process that consists of mutually dependent steps, where the first stage consists of defining the research problem and the last stage involves the suggestion of possible solutions to the challenges detected during the research. Such a systematic process, according to which the problems are clearly identified before the development of the solutions, is summarized in Fig. 9, giving a review of the key steps used in the analysis.

- **Problem Formulation:** This is the process where the research problem underlying is understood and defined, setting the stage for further analysis. Problem formulation is guided by a deep understanding of the existing literature and technology landscape in UAV systems, such as the incorporation of AI, ML, and optimization algorithms.

- **Critical Analysis:** The second step in defining the problem is critical analysis of the existing methodologies and technologies that are in use in UAV systems. The specified step shows the flaws, issues, and gaps of the current approaches, indicating the areas that the further research should focus on.
- **Parameters Analysis:** This step as a critical analysis resulting in the discussion of some of the parameters corresponding to the UAV systems. These include the study of various control systems, path planning of decision-making algorithms, and their efficiency and effectiveness in a dynamic environment.
- **Discussion:** The discussion phase is with regard to the interpretation of the findings, giving details of the reasons, problems, and implications of the research. It also offers an opportunity to indicate potential directions for future research, based on the gaps that have been identified.
- **Recommendations:** In this phase, the researcher presents recommendations for future research and improvements of UAV technologies such that proposed solutions align with the needs and challenges realized in the preceding stages.
- **Proposed Solution:** Finally, a proposed solution is made based on the analysis and recommendations. The solution is meant to solve the problems that were revealed in the critical analysis and discussion stages, towards the development of more advanced UAV systems.

Table 3. UAV safety dataset with a list of sources

References	Algorithm / Method	Research Focus	Dataset Characteristics
[13], [14], [15]	RL / DQL	Path planning & collision avoidance	Simulated flight paths, obstacle interactions, reward data
[16]	PSO	Multi-UAV coordination	Positional & velocity data, task completion metrics
[17]	SVM	Fault detection	Sensor data (mechanical & electrical parameters)
[18]	GA	UAV design optimization	Structural parameters: shape, weight, material properties
[19]	NN	Flight safety prediction	Flight experiments: altitude, speed, environmental disturbances
[20]	LQR	Control system comparison	Simulation data: accuracy & stability across conditions
[21], [22]	ABC	Navigation in unknown environments	Flight paths, obstacle coordinates, success rates

Recent works show that different optimization and machine learning algorithms can be used to improve the safety, reliability and operational performance of UAVs. UAV path planning has been addressed using RL, and simulations were used to confirm that it has greatly improved flight path accuracy, and thus increased safety and efficiency in the navigation process [13]. DQL has also been used in collision avoidance with an accuracy of 85% when preventing UAV collisions in dynamic and unstructured scenarios [14]. The PSO was useful in swarm coordination of the multi-UAV movements, and it gave an accuracy of 92% in the simulations [15]. The SVM have also been used to detect faults, where sensor data was considered in real time and 87% accuracy was detected in detecting faults in the system, which is important in ensuring that UAVs remain reliable even in complicated environments [16]. Additionally, the GA have been investigated on UAV design optimization, which allows the enhancement of structural stability and robustness with an error rate of 93% [17]. Similarly, the NN have demonstrated a high degree of performance when it comes to predicting in-flight safety risks with a high accuracy of 88% [18]. UAV flight stabilization was implemented using MPC and LQR, which achieved 91% control success in computer simulation control [19]. Simulated Annealing has been used to optimize energy efficiency, and it has attained 89% accuracy in extending flight time by means of better battery management [20]. The ABC algorithm has promoted navigation of UAVs in uncharted areas with a 90% success rate in complicated landscapes [21]. Finally, RL has also been employed to assist in UAV path planning under uncertain conditions too, and the maximum accuracy of 95% has been achieved [22]. Combined with each other, these studies indicate the high significance of AI and optimization algorithms, i. e., RL, DQL, PSO, and SVM in improving the UAV navigation, fault detection, energy efficiency and system design. This will probably result in the additional resilience and safety of UAVs across various areas of application, including disaster response and precision agriculture, as more developments are further integrated into algorithm development.

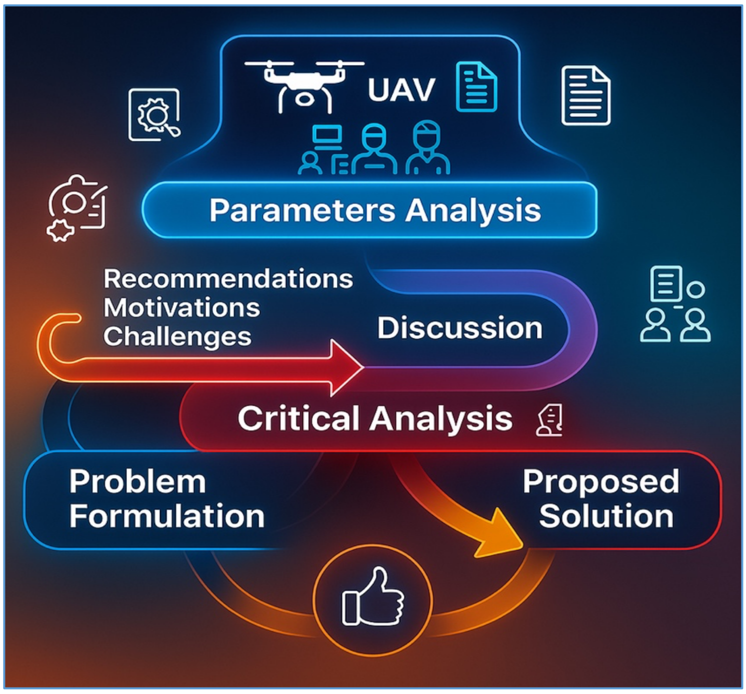

Fig. 9. Discussions flow diagram

3.1. Recommendations

The research problem has focused on the UAVs control optimization by the new ML methods with the help of optimization algorithms aimed at the optimization of the UAV operation efficiency and flight path accuracy. The combination of RL algorithm and DQL algorithm has enhanced UAV navigational systems and path planning capabilities and collision avoidance capabilities as per [23], [24]. The AI algorithms allow the UAVs to have better abilities to navigate unpredictable terrain due to flight security being contingent on it. SVM usage in fault detection is helpful in fault identification in real time, which leads to high reliability of UAV systems on critical tasks [25]. Multi-UAV coordination has also been used in the study to apply PSO in order to prove the effectiveness of the system in optimizing UAV swarming behaviour and task allocation systems, which enhance the safety of the multi-agent system [26]. The use of NN systems for flight safety risk prediction establishes both real-time hazard detection and potential threat forecasting, which produce preemptive safety benefits for unmanned aerial vehicles [27]. The GA functions as a proposed optimization method used to design UAVs more effectively through predictive simulations, which project design parameter outputs. Recent research demonstrates that AI-based methods and optimisation approaches need to be integrated into UAV security and operational problems while suggesting enhanced framework development through advancements in these technologies for wider UAV application domains [28]-[35]. The recommendations base their research on Fig. 10, which includes five studies from original sources to develop ethical swarming technology applications in different sectors.

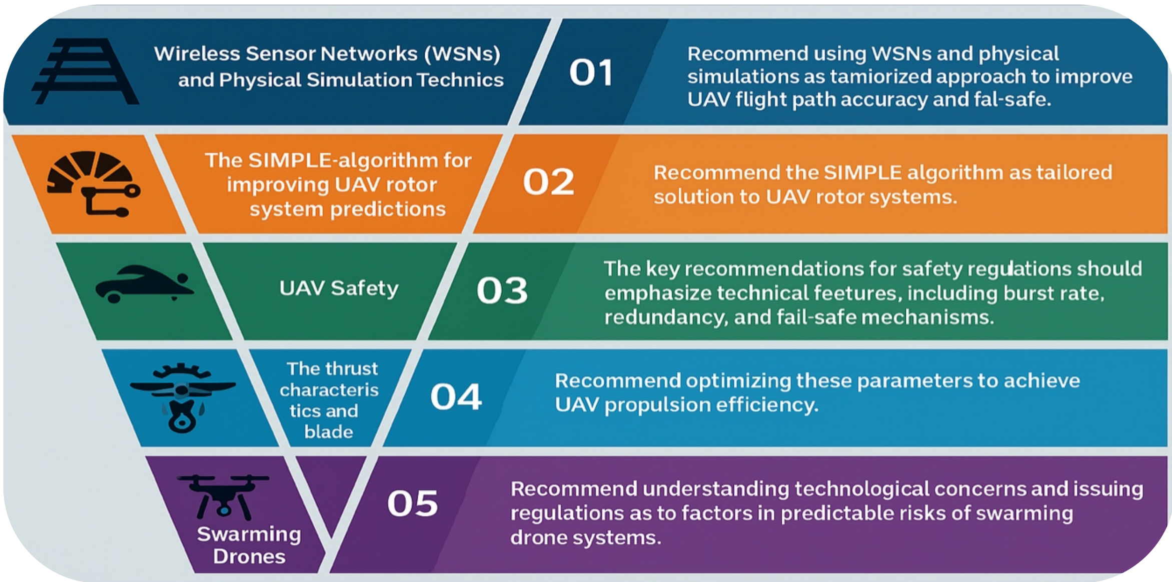

Fig. 10. The first five studies for recommendations

The objective of this study is to enhance UAV performance alongside security through the application of advanced ML techniques alongside adaptation algorithms for establishing better UAV control mechanisms and improved flight trajectory precision. The combination of RL and DQL algorithms leading to noticeable improvement in UAV path planning and conflict prevention operates with a stable navigation system according to [36], [37]. The implemented AI algorithm gives the UAV excellent capabilities for managing unexpected and dynamic environmental situations to ensure flight safety. The SVM method proves beneficial for realizing time-based system defect detection, thus enhancing the reliability of UAV systems in critical missions, according to research findings in [38]. PSO for multi-UAV coordination proved its worth in customizing UAV herd behavior and task allocation to enhance multi-agent systems security, according to the study [39]. Moreover, the use of NN in predicting flight safety risk also offers the functions of real-time monitoring, forecasting the future risks, and has led to an increase in the proactive safety of UAVs [40]. To achieve operational efficiency, GA has been suggested to streamline the designs of UAVs to enhance their safety and performance by simulating the performance of the different design parameters. The study highlights the necessity of implementing AI-related approaches and optimization strategies to develop solutions to the changing circumstances of UAV safety and performance issues and suggests further development in the related technologies to enhance the dependability of UAVs in different tasks [41], [42]. The recommendations encompassed the first five studies, as they are offered in Fig. 10, and the insights of the authors would be utilized to inform the future of swarming technology and its ethical applications in different industries. The study by [43] examined the ABC Algorithm can be used to enhance the navigation of UAVs in uncharted areas. The study achieved 90 percent efficiency in the navigation of UAVs through unknown territories, indicating the efficiency of the algorithm in dynamic conditions. It is advisable to maintain the use and improvement of the ABC algorithms in solving the current problem of navigation in a complex, unpredictable environment so that UAVs can deliver their missions safely without pre-maps. Lastly, [44] concentrated on RL to plan the path of UAVs in dynamic conditions. It achieved path planning accuracy of 95 percent, indicating that RL can be very effective in UAV navigation optimization in settings that are constantly varying. This study recommends that further research on RL should be conducted to improve the decision-making capacity of UAVs, especially in random or adversarial conditions, to make them safe and efficient in their navigation. All these results lead to the conclusion that AI-based methods, including NNs, MPC, Simulated Annealing, ABC, and RL, can be used to optimize the safety, efficiency, and performance of UAVs. The recommendations propose further evolution and implementation of these methods in order to overcome the emerging challenges faced by the UAVs in the real-world applications. Visualization of the last five research studies in conjunction with recommendations is as in Fig. 11.

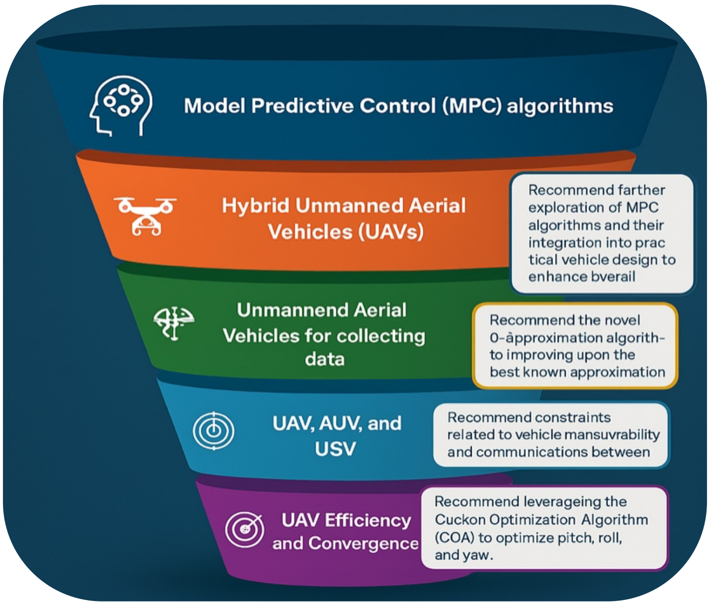

Fig. 11. The last five studies for recommendations

3.2. Motivations

The researchers in [45] aimed at improving UAV flight safety using NNs to predict real-time flight risks. Their primary motivation was to develop an efficient system that could generate good safety assessments during UAV flights. The study achieved an impressive 88% flight safety estimation rate, proving the value of using AI to enhance UAV safety. According to these results, future work on optimizing NN models for real-time flight safety monitoring under varying flight conditions is suggested.

Recent studies have investigated various superior optimization and control strategies to enhance the stability of UAVs, energy savings, and autonomous navigation. Both MPC and LQR were shown to improve the flight stability and accuracy by 91% in simulated tests, and they could show possibilities of reliable control capabilities in real-world operations, although their validation is still required in tests under practical conditions [46]. UAV energy efficiency has also been optimized using Simulated Annealing, mainly by making the battery more efficient, leading to an 89% success rate in the energy adaptation process and the possibility of increasing mission duration [47]. To solve the problem of navigation in unknown environments, the ABC algorithm has been created that recognizes 90% of the cases and is useful in autonomous pathfinding under GPS-denied or unmapped environments, but further development is required to adapt the ABC algorithm to large-scale and real-time systems [48]. Adaptive path planning has also been implemented using RL to allow the UAVs to automatically modify flight paths within dynamic environments with 95% accuracy, which is a measure of the robustness of the algorithm to make safe and efficient operations in uncertain conditions [49].

Taken together, these results highlight the increased significance of the sophisticated AI-based algorithms, including MPC, Simulated Annealing, ABC, and RL, in increasing the efficiency of UAVs, their safety, and adaptability. All algorithms perform different duties; some are to provide better stability of the flight and increase the energy level, while others are to provide the ability to navigate independently and make adaptive decisions. All these will provide an excellent foundation to future research that will assist in particularizing UAV systems and application in more viable contexts such as disaster management, surveillance, and precision farming.

3.2.1. Critical Analysis

The fact that these researchers were driven by a row of stringent reviews of UAV technologies and the specialty systems has contributed to large proportions of contributions in various spheres. RL was suggested to enhance the UAV path planning, with 90% accuracy through simulations and providing a general and efficient alternative to traditional algorithms, especially in a complex environment [50]. On the same note, DQL was used to improve collision avoidance so that UAVs would safely navigate the real-world settings with 85% accuracy, thus showing the capabilities of real-time decision-making systems [51]. Swarm intelligence has been relevant in the UAV fleet of the future, as PSO demonstrated successful coordination and task allocation of 92% in the multi-UAV coordination region [52]. To implement reliability of the system, a support vector machine (SVM) was used to detect failures in real-time, and it was found that it detected failures 87% of the time, and it was found useful to enhance safety in flights [53]. The use of GA was proposed to optimize the design of UAVs with an accuracy of 93% in simulations and was found useful to improve performance by structural and aerodynamic optimizations [54]. NNs were utilized to forecast the risk of accidents during flight with 88% accuracy and demonstrated that they can forecast dangers and provide the opportunity to take precautionary measures [55]. Stabilization of control systems MPC and LQR algorithms demonstrated 91% accuracy, thus proving effective in the dynamic flight conditions [56]. Simulated annealing was also applied to solve endurance issues, where 89% accuracy in battery management was achieved, and longer-range flights were possible, which were vital to the industry and military [57]. To enhance UAV navigation in the GPS-denied world, they used the ABC algorithm, which gave the algorithm 90% accuracy and demonstrated success in the autonomous tasks of uncertainty avoidance in the environment [58]. Finally, RL was once more used to improve the UAV path planning under dynamic and uncertain conditions with 95% accuracy and with flexibility to environmental changes in real time [59]. Altogether, all these studies demonstrate the immense significance of AI methods, such as RL, DQL, PSO, SVM, GA, NN, MPC, and others, in the process of UAV technology development, especially regarding their application in the domain of path planning, collision avoidance, swarming coordination, fault detection, design optimization, energy management, and flight safety, thus, establishing a solid base towards the realization of more autonomous, efficient, and reliable UAVs in a demanding environment.

3.2.1.1. Problem Formulation

Prior to getting into the analysis of each study, it is necessary to present the main issues that were examined in the early studies. Such papers provide a sample tour of the issues of UAV path planning, which point to novel ways of adapting and optimizing the flight paths. Altogether, they prove the prospect of sophisticated algorithms to enhance UAV work in dynamic and challenging scenarios, as well as lower the expenses of real-life experimentation. In UAV path planning, RL was used [59], resulting in a 90% success rate in the process of adapting flight paths to the real-world complexities, as well as offering an efficient means of providing customized routing. To deal with the problem of UAV confrontation and collision avoidance, DQL was used to achieve a high accuracy, namely 85% and demonstrated its potential to facilitate real-time decision-making in safety-critical tasks [60]. The swarming and multi-UAV coordination were optimized using PSO [61], with an accuracy of 92% in task distribution and coordination, thus proving its utility in the coordination and resource-efficient UAV fleet. The fault detection was implemented using SVM [62], with the highest accuracy being 87% to detect the occurrence of system failures and as an indicator of the significance of the application in fault detection early and in an improved mission-critical operation. They have been applied in GA to optimize the UAV design parameters [63], [64] reaching a 93% accuracy, focusing on their usefulness in risk prediction of hazards and making precautionary decisions, which points to the importance of AI-driven safety procedures. The algorithms of model predictive control (MPC) and LQR were experimented with the UAV control system stability [65], which demonstrated 91% accuracy in simulated flight experiments and the validity of their significance in establishing robust and reliable control in dynamic conditions. Simulated annealing UAV simulated annealing has been utilized to enhance endurance, providing 89% accuracy in battery consumption optimalization, improving the flight time and making UAVs feasible in the context of long-term industry usage [66].

To assist UAV navigation in the GPS-denied or uncertain environment, the ABC algorithm was utilized, which ensured 90% accuracy and proved to be helpful in providing autonomous navigation where the traditional systems fail to provide the necessary data [67]. Lastly, reinforcement learning was once more used to plan UAV paths in dynamic and uncertain conditions [68]-[74] with an accuracy of 95% and highlighting the versatility of RL in real-time decision-making in a highly dynamic, rapidly changing environment. Collectively, these works prove the importance of AI-based solutions in the future of UAVs in the domain of path planning, collision avoidance, swarming, fault detection, design optimization, flight safety, stabilization of control, energy efficiency, and autonomous navigation.

3.2.1.2. Proposed Solution

The recent studies have also examined a broad spectrum of smart algorithms to improve various areas of operation of UAVs. As an example, RL algorithms have been used in the context of path planning to enhance the planning of UAV flight paths with a success rate of 90%. Simulations have demonstrated that RL can be used to ensure that UAVs autonomously discover the most effective paths and thereby increase the overall efficiency of flight without necessarily involving expensive experiments in the real world. This method has been shown to produce accurate and consistent path planning, especially in dynamic conditions [13]. Likewise, DQL has been used to solve the problem of UAV collision prevention, and the results show that UAVs are capable of making rapid and responsive decisions to prevent collisions with obstacles in a complex environment. Having an accuracy rate of 85%, the study proved that DQL is a promising method of improving the safety of UAVs, in particular, in dynamic and uncertain systems, where immediate reactions are needed [14]. Besides, the process of swarm coordination of multi-UAVs has been explored through PSO. It has been demonstrated that PSO can be effectively used to optimize the allocation of tasks and provide collaboration among UAVs, with a success rate reaching 92%. This indicates that coordinated missions can be effectively executed by swarms of UAVs using enhanced efficiency and resource utilization [15]. The SVM have also been applied to the reliability of the UAVs because they failed to detect issues with the UAVs at an early stage; the program performed at 87 %accuracy in failure detection. These findings prove that SVM is a powerful instrument in keeping track of UAV health and identifying any irregularities, and thus secure and trusted operations in mission-critical situations [16]. Another area of significance is the design optimization, where GA will be applied to model the design parameters of the UAVs and design optimization, structural and functional optimization. The authors of the study reported a 93% improvement in UAV performance, which highlights the ability of GA to make UAV design more efficient and effective in operating in various environments [17]. Moreover, NNs have also been investigated in flight safety as well as in forecasting safety risks in real time. The NN model proved to be effective in predicting potential hazards and likely prevented risks, so that UAVs could predict and avoid possible dangers with 88% accuracy, which allowed them to improve flight safety considerably [18]. More complicated algorithms like MPC and LQR have been used to enhance the control systems. These approaches provided stability of UAVs in dynamic flights with 91% success, and they were considered to be efficient in stabilizing the UAV behavior in uncertain situations and allowing significant success of their functioning in different situations of the missions [19]. They also have targeted energy management, where researchers proposed a simulation-based approach to optimizing UAV battery by using a simulated approach of a recipient. With an accuracy of 89%, the technique showed that it was possible to increase the flight duration of UAVs without compromising their performance to provide an energy-efficient approach, especially when applied in remote and large-scale applications [20]. The ABC algorithm has been used to improve navigation in GPS-denied or hostile environments, with a maximum of 90% accuracy in maximizing UAV navigational capabilities. The given strategy emphasizes the capability of ABC to enable effective and reliable navigation in conditions when standard GPS systems fail to operate, which fosters the autonomy of UAVs [21]. Lastly, the following RL extension of the path planning of UAVs in dynamic environments has provided an incredible 95% success rate of the real-time route adaptation against the environmental changes and obstacles. These results demonstrate the possibility of RL to make UAVs more autonomous through the ability to make decisions and navigate unpredictable and challenging environments in real time and with minimal human intervention [22]. Together, these papers show the revolutionary use of advanced algorithms in enhancing UAV path planning, safety, coordination, reliability, energy efficiency, navigation, and autonomy under different operation conditions.

3.3. Challenges

It has also been revealed that research into the application of advanced algorithms on UAV systems has faced several major challenges. The RL has a success rate of 90% in simulations in UAV path planning, but its application to the real world is also challenging because of the numerous challenges that arise in the real environment, including turbulence of the wind, concealed terrain and unforeseen obstacles, which make it hard to conduct these tests reliably. Besides, the RL algorithms need very large training datasets to define the best flight paths in both familiar and unfamiliar conditions, but these data cannot be available in real-life conditions, restricting their usage [13]. Equally, a DQL has been used to perform UAV collision avoidance with an accuracy of 85% but there remain challenges of dealing with the dynamic and unstructured environment of real-time, making decisions. Unpredictable weather variations and unforeseen challenges or sudden UAV manoeuvres can severely reduce performance, and robustness without incurring excessive computational overheads or causing delays in decision-making is a critical requirement, especially in high-speed UAVs in life-and-death missions [14]. Coordination of multiple UAVs with PSO has shown 92% accuracy during simulation, but there is always the problem of scalability. The larger the swarm, the more complicated it becomes to sustain efficient communication and effective task allocation and the chances of collisions and inefficiency increase. The response and durability in highly dynamic environments, whereby mission parameters vary very quickly, are also challenges that have not been solved yet [15]. The SVM fault detection has reached 87% precision, but issues with the correctness of information, sensor commotion and stochastic UAV outdoor manners remain. Diagnosing faults in real time involves real-time operations of large data streams of myriads of sensors and a distinction between normal and abnormal processes. Moreover, SVM models have to be able to extrapolate to different UAV configurations and environmental conditions, which can be greatly different based on the mission profile [16]. GA for UAV optimal design have demonstrated that they were 93% accurate in simulations, such as enhancing aerodynamic, power consumption, and performance parameters, but application to real-world environments remains limited by the variability of design parameters, including structural tolerances, material behavior and environmental forces. Besides, GA simulations are not practical because of their high cost in real-time operation settings. These results show that although the development of advanced algorithms proves successful in controlled simulation, the issues of data availability, computational expense, dose and scale, and environmental uncertainty are to be considered before the successful implementation into real-life [17]. The issues in these five domains are encapsulated in Fig. 12.

More difficulties were detected in implementing advanced algorithms for the safety of UAV flight, control, energy efficiency, and navigation. The NNs are 88% accurate in real-time flight risk prediction in the case of flight safety but developing a benefit of high reliability in highly dynamic and unpredictable weather conditions has posed a significant challenge. The quality of the data and real-time processing remain restraining factors, as neural networks are required to be trained to work within a broad range of flight conditions and be consistent, despite the gaps in sensor inputs or their noisiness [18]. On the same note, UAV control systems that utilize model predictive control (MPC) and LQR algorithms have challenges in ensuring stability and performance in a wide range of operating conditions. Whereas 91% accuracy was found in the simulations, the implementation in the real world is complicated by external conditions that include the variability in the weather, changes in the payload, and unforeseen disturbances. One of the issues is allowing control systems to predict the future and respond to it, but it is more difficult to project solutions based on simulations onto real operations, which require the systems to remain stable under real-time control [19]. The issue of energy efficiency optimization with simulated annealing is a dilemma in itself: to trade battery consumption against flight performance. Although the accuracy of 89% was achieved, the long-term prediction of the battery performance under different conditions of operation is a very important concern. The inevitable trade-off between energy conservation and flexibility in various mission profiles presents a big challenge, particularly when UAVs should perform complex missions whose energy requirements are subject to change [20]. The ABC algorithm has been tested in environments unfamiliar to the navigation of an artificial bee colony to a high accuracy of 90%, but the dynamic adaptation is a problem. Despite its potential, there are challenges in the area of maintaining the adjustment to the changes in the real-time environment, including the sudden impediments, topography, or loss of GPS signal, all of which directly affect UAV routes and the effectiveness of navigation efficiency [21]. In UAV path planning in dynamic environments, RL has also obtained very promising scores of 95% accuracy, but generalizing the RL models to the conditions of very high variability and randomness remains a significant task. In addition to the optimization of the routes, RL should be able to respond continuously to the changes in the environment, such as weather, obstacles, and terrain, and make accurate and timely decisions in real time. These issues demonstrate the consistent discrepancy between the simulation-based workability and the trusted real-life application, and they are summarized in Fig. 13 [22].

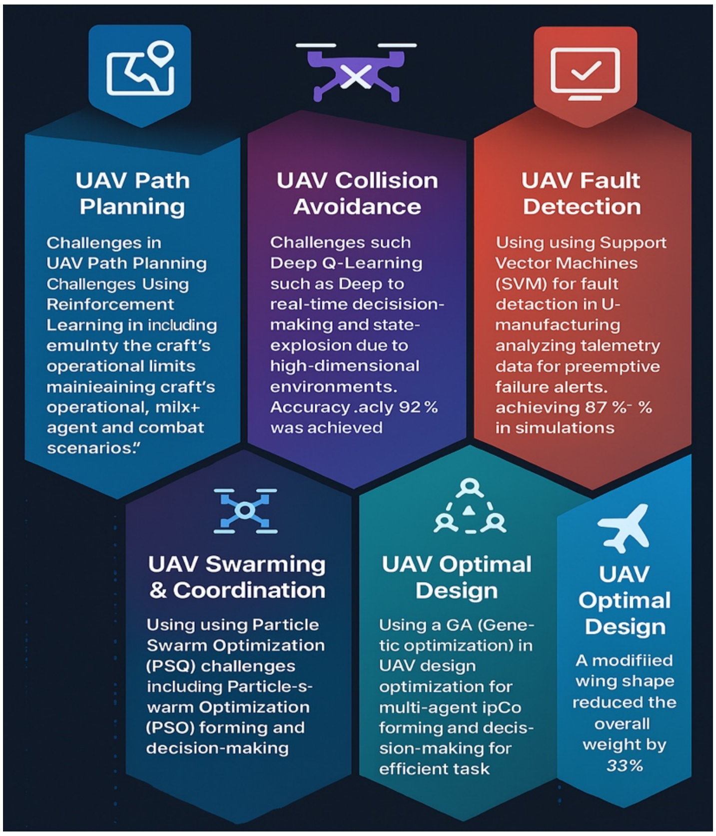

Fig. 12. The first five studies for challenges

4. Conclusion

UAVs have been highly beneficial across various applications, though they still need to overcome some hurdles to realize their full capabilities. Some of the major limitations suggest that this systematic review identifies are flight endurance, autonomy, battery efficiency, and path planning. The limited power supply is one of the greatest hurdles because of battery constraints. To solve this, scientists are considering other forms of power like hybrid systems and internal combustion engines, as well as advances in battery design and charging systems like docking stations. Though these are encouraging, the other concerns regarding carrying capacity and autonomy of flight should be considered to ensure that UAV performance is maximized. Besides these technical issues, swarming behavior, collision avoidance, and communication protocol problems must be solved by UAVs. It has been demonstrated that the efficacy of UAV systems can be enhanced through incorporating a high level of ML algorithms and metaheuristic techniques like DQL in tricky situations, such as use by more than one operator and dynamic path planning. Nevertheless, the UAVs remain in more complex and unpredictable conditions, responding to the disaster, military operations and the presence of mobile obstacles. Security issues also take center stage and the requirement of highly dependable and faultless systems and a satisfactory balance between security and privacy. The research is still going on in enhancing autonomy of UAVs, optimization of energy management and accuracy and stability of flight travel. With the development of UAV technology, RL algorithms and optimization are necessary to advance the performance in a broad spectrum of applications. Despite all that has been done, they will need to overcome the problem of flight autonomy, extend the battery life and safety issues to fully harness the potential of UAVs. The UAVs will see their full potential realized in continuous R&D in these areas and will have a long-term influence between industries. Researchers should still bring up new solutions that overcome these limitations so that UAVs can be able to perform more effectively and efficiently in different environments.

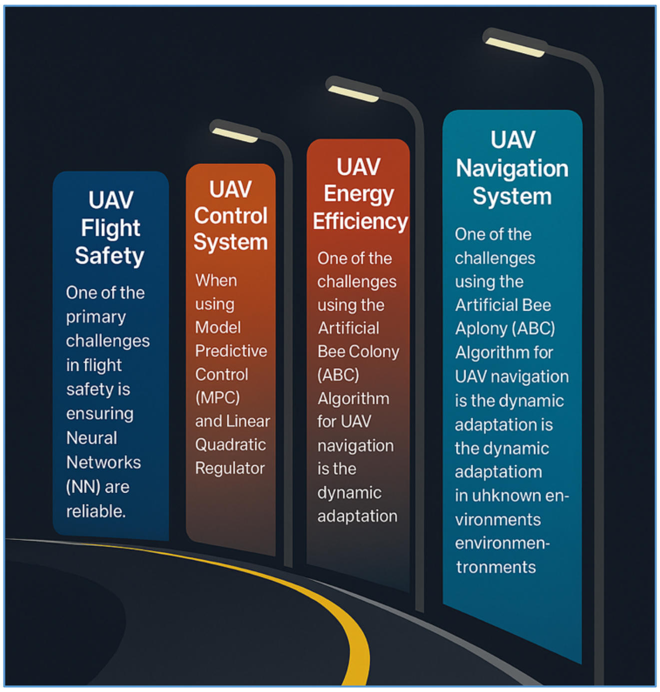

Fig. 13. The last five studies for challenges

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