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An empirical analysis of UAV routing models from a context-specific statistical perspective

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Abstract: Despite the power constraints, UAVs (Unmanned aerial vehicles) have an inherent advantage of lower air traffic, making them an attractive alternative to high-speed transportation and logistics. Many algorithmic models are used for empirical analysis based on network architecture, data forwarding, and comprehensive performance variation regarding routing delay, energy efficiency, throughput, network overheads, scalability, bandwidth, link failure probability, etc. Due to such a wide variation in protocol availability, and respective performance measures, it is difficult for researchers and network designers to select the best possible models suited for their network application. Moreover, this wide variation increases network design time and cost-to-market, which affects UAV network viability. Thus, there is a need to simplify this process of routing model selection. This motivates us to frame this survey article. A comprehensive survey of recently proposed UAV routing models is proposed. This survey includes a description of reviewed models and their nuances, advantages, limitations, and future research possibilities. Upon referring to this survey, readers could contemplate the characteristics of respective models and identify improvement areas in each. Based on observation, researchers can select the best-suited routing models of UAVs for their applications. This review is accompanied by an in-depth statistical analysis of these models and their comparison concerning computational complexity, throughput, energy efficiency, end-to-end delay, and routing efficiency. It will assist researchers and UAV network designers in selecting the most optimum context-specific models for their network deployments, thereby lowering network design time and cost of deployment.

Keywords: UAV,Routing model,Path planning,Energy efficiency,Delay,Throughput.

1. INTRODUCTION

In recent years, the growing demand for Internet access from various devices has challenged companies and academics to research and develop new solutions that support the increasing flow in the network, applications that require very low latency, and more dynamic and scalable infrastructures. In this context, mobile ad hoc networks (MANETs) emerged as a possible solution, and applying this technology in unmanned aerial vehicles (UAVs) has emerged as a potential application (FANETs).

Drones and other aerial vehicles were first created for the aerospace and military sectors. Still, due to their rising effectiveness and safety, the general public can now utilize them. These unmanned autonomous aerial vehicles (UAVs) fly by themselves. While a drone may be controlled remotely, it can also be fitted with sensors and LIDAR detectors that give it autonomy. The model determines the height and distance that drones may fly. The standard operating range of amateur drones is three miles or fewer. The maximum flying distance for this type of aircraft is 30 miles. Drones, which range of up to 90 miles, are mainly used for intelligence gathering and surveillance. Mid-range unmanned aerial vehicles have a range of 400 miles and may be used for several tasks, such as scientific research, information collecting, and meteorological studies. The ”endurance” UAVs, which have a maximum range of 400 miles and can fly up to 3,000 feet in the air, are the drones with the greatest range.[1], [2], [3], [4]

Because of their versatility, flexibility, easy installation, and relatively small operating expenses, UAV path planning is a multi-domain task that involves node localization, traffic estimation, environmental condition estimation, path prediction, etc. These routing models are classified into cluster-based or swarm-based methods. The cluster-based methods utilize either one-hop or multiple hop models, while swarm-based processes utilize ant-colony (ACO), bee-colony (BCO), particle swarm optimization (PSO), and similar methods. These methods aim at route optimization during path planning via stochastic modeling, which assists in the reduction of routing delay, battery costs, energy consumption, etc. A typical UAV path planning model is described in figure 1, wherein swarm optimization-based

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stochastic approach is describe[5]. The model is initialized

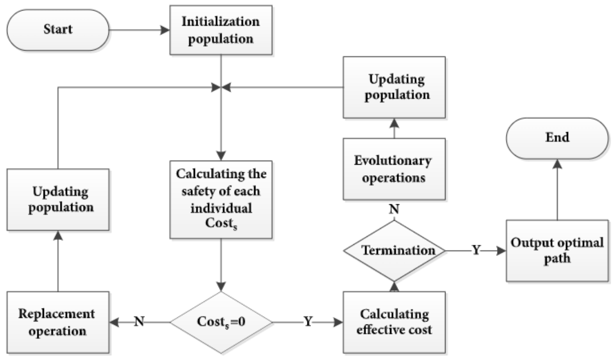

Figure 1. Swarm intelligence model for UAV path planning

via generating random trajectory-based augmented solutions between source and destination points. A fitness value for each of these solutions is estimated via equation 1, wherein parameters like distance travelled (D), the energy required (E), path quality (PQ), etc., are used for calculations.

$$f_p = \sum_{i=1}^{N_h} \frac{D_i}{Max_D} + \frac{Max_E}{E_i} + \frac{Max_{pQ}}{PQ_i} \ldots \quad (1)$$

Based on these values, Other solutions (population) are updated, or new solutions are created based on these values. These solutions are reiterated via fitness checks to estimate the best route between two points. Researchers propose a wide variety of models to perform these tasks. A Survey of these models and their nuances, advantages, limitations, and future research scopes are discussed in the next section of this text. Upon referring to this section, researchers will be able to identify best practices for UAV path planning and use them to design routing models for their networks. The rest of the paper is organized as follows: Section 2 discuss the existing related works, and in section 3, a Statistical analysis is presented pertaining to UAVs routing protocols. A brief discussion of the model is presented in Section 4. Finally, Section 5, concludes with interesting observations about the reviewed models and recommends methods to improve their performance in different scenarios.

2. Literature Review

Researchers have proposed many drone-based routing models to improve route quality and reduce drone flight delays. These models vary in application-of-use, routing efficiency, delay needed for coverage, etc. For instance, the work in[6] proposes a multi-parameter model (MPM) that uses the angle of rotation, the distance between source & destination, the number of obstacles, and inter-obstacle distance, to estimate a trajectory path. This path approximates the optimum path, and its selection can be enhanced using bio-inspired models. Due to such an approximation, this model's delay increases linearly with respect to the number of nodes in the network, making it non-scalable for real-time deployments. This model performance can be improved using bio-inspired computing methods proposed in[7].

This paper uses a genetic algorithm for Routing (GAR) and modeled with a fitness function that uses route quality (RQ), distance (D), and energy needed for trajectory between source and destination points E_{SD}. This fitness function can be evaluated via equation 1 as follows,

$$f_{i,j} = w_1 * RQ_{i,j} + w_2 * D_{i,j} + w_3 * E_{i,j} \ldots \quad (2)$$

Where, w_1, w_2, w_3 represents weights for route quality, distance and energy between the nodes. Due to this modeling, the system can reduce control overheads & delay when compared with ad-hoc on-demand distance vector (AODV) and dynamic source routing (DSR) models. Another heuristic approach that uses K-Means and Integer Linear Program (ILP) is proposed in[8]wherein researchers have extended GA to incorporate clustering and deterministic models. Due to this extension, the proposed GAILP model can find paths with lower delay and better energy efficiency when compared with the K-Means & ILP approaches. But the model requires multiple scenes modeled parameters for routing, which increases its deployment complexity & reduces its energy efficiency. In order to improve this efficiency, work in[9] proposes an energy-aware approach, which uses swarm intelligence with a minimum spanning tree (SIMST) for removing redundant route vertices. Due to this, the model showcases 40% lower energy requirements when compared with the distance-based trajectory (DTJ) method while requiring a similar delay for covering a low to medium number of path points. But the model has limited scalability due to its deterministic nature and applicability for object checking. The scalability can be improved using sampling, AI, bioinspired, machine learning-based, multiple objective optimizations based, and non-cooperation-based models as discussed in[10].

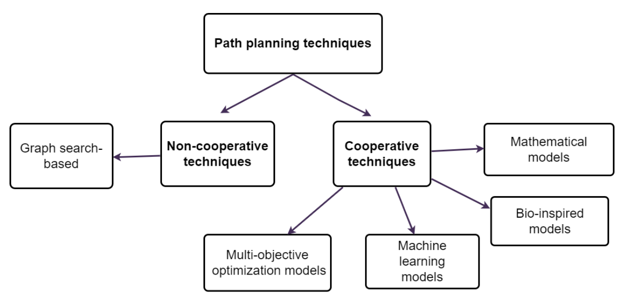

Figure 2. Classified UAV path planning techniques

UAV path planning is classified into two categories, namely comparative and non-cooperative. The algorithms include genetic algorithms, evolutionary models, simulated annealing method, and ant colony optimization (ACO), to name a few. It is observed that reinforcement learning and multiple objective optimizations outperform other models in terms of path quality and energy efficiency. A classification technique is described in figure 2, wherein various UAV and path planning models are visualized and observed. Based on this observation, the work in [11] is reviewed, which suggests a multiple objective UAV (MOUAV) path planning approach for emergency information transmission & collection. This model uses UAV path gain updation mechanism to maximize the channel capacity for path planning. It also proposes different UAV coverage update mechanisms and single waypoint planning to incorporate buffer distance, essential wind speed, angular components, air density, Gravity acceleration, drag coefficient, moment of inertia, fuselage radius, thrust coefficient, and torque coefficient parameters. Due to incorporating so many metrics for path planning, the proposed model is observed to have 20% lower energy requirement & flight time when compared with conventional models, which makes it highly scalable for a wide variety of drone-based environments.

Another bioinspired (BI) model that uses a sparrow search algorithm & Neural Network (SSANN) is proposed in[12] wherein researchers have deployed path planning methods for multiple UAV nodes. It combines B-spline curves with safe surface cost optimization to reduce the distance & energy needed for routing. The flow of the model is described in figure 3, wherein SSA, B-spline, and bioinspired NN methods are visualized. The model uses a

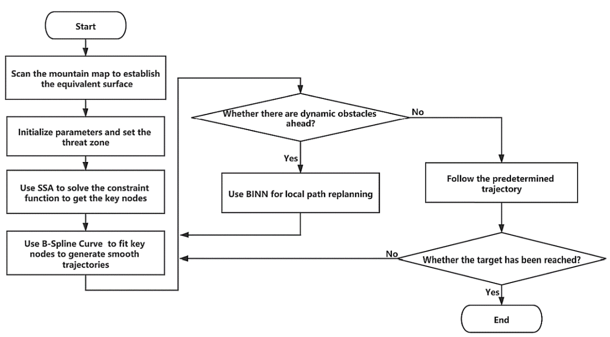

Figure 3. Combination of SSA with NN for improved efficiency of routing

combination of deterministic and probabilistic approaches to improve the speed and lifetime of the UAV network. The model also showcases better path quality, smaller path lengths, and lower flight duration when compared with these methods. The model has an average success rate of 98 % which is higher than artificial bee colony (ABC) optimization (53 %), and Dragonfly Algorithm (DA) (62 %), when compared on the same simulation platforms.

A scale-invariant feature transform (SIFT) based model that removes collision areas during routing via imaging techniques is proposed in[13]wherein a support-vector machine (SVM) based classification engine is used. The proposed model requires large image data (60% of the entire area) to generate an optimum path but achieves better efficiency in terms of coverage & route quality. To reduce dependency on image-based coverage, in [14] proposes a multiverse optimizer (MVO) model that uses node to node distance, colliding path sets (CPS), node moving rate, threat probability, and possible path list for resultant path selection. The model is observed faster than ant lion optimization (ALO), DA, Moth flame optimization (MFO), whale optimization model (WOM), and grey wolf optimization (GWO) approaches, which makes it useful for small to medium scaled routing applications. But the model has limited scalability, which can be improved via multiple parameter analysis as suggested in [11], wherein a large number of model inputs are considered for path planning. A scheme is proposed in [15], where a completion time minimization approach is proposed, that uses Schur complement & semidefinite programming models for ensemble route estimation. It combines various heuristics to reduce completion delay and improve overall routing throughput, making the model highly scalable for a wide variety of routing scenarios.

In contrast, a highly application-specific model for a mission-oriented approach for path planning that uses solar-powered (low power) UAVs for high altitudes is proposed in [16], wherein optimal energy management approaches are utilized. The proposed model uses multiple parameters that include vehicle mass, Sun's Azimuth Angle, angle of Sun's Altitude from the center of Earth to centre of Sun, Airspeed, efficiency of photovoltaic Nodes, Motor efficiency, battery efficiency, propellor efficiency, flight path angle, its bank angle, heading angle, & attack angle, the density of air, wing area and load power to estimate an optimum mission specific routing path. It is possible by using the augmented Multiple Goal Path Optimization (MGPO) model as observed in figure 4, wherein both point-to-point optimization & MGPO are combined. The model optimizes climbing, high altitude cruising, gliding, and low altitude cruising operations with 15% lower power when compared with the fixed constraints path model (FCPM), thereby making it useful for a wide variety of application-specific routing scenarios. Another model that uses a similar approach for stealth UAV applications is proposed in [17], wherein researchers have used an improved A-Star algorithm (IASA) to include dynamic radar cross-section characteristics into flight planning. The model can reduce the distance covered, the power needed, and the delay for routing compared with A-star (AS) and D-star (DS) models, making it applicable for various path planning scenarios. An extension to this approach is proposed in [18], wherein ANN is used for controlling AS, set-based PSO (SPSO), and k-agglomerative clustering (kAC), to improve routing performance. The model initially uses K-Means & KAC for coarse Graph generation, which is fine-tuned via the A-star model. This fine-tuned Graph is given to an SPSO model, which assists in final path planning via analysis of multiple parameters like moment of inertia, node-to-node distance, etc. Due to this, the model is observed to have better efficiency when compared with proportional integral derivative (PID), fuzzy control, PSO with swap, SPSO with chaotic inertia weight, and SPSO with adaptive weighing measures.

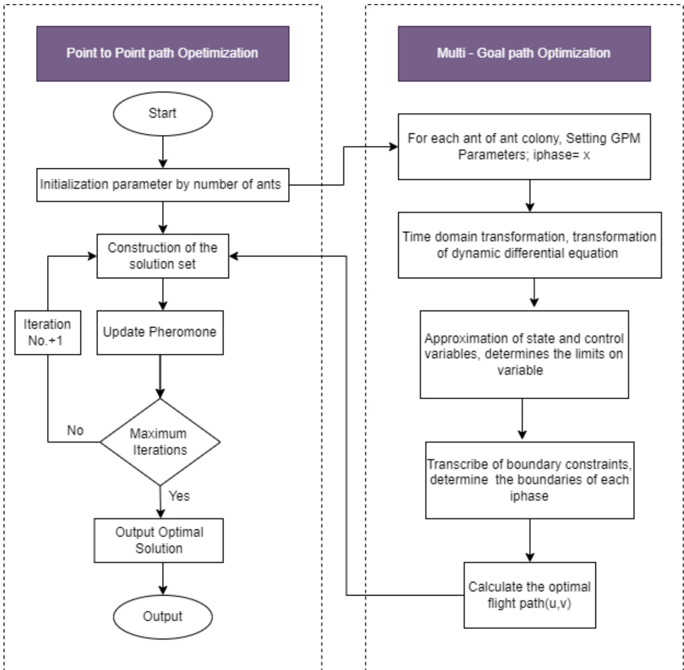

Figure 4. Augmented MGPO model for efficient path planning

A similar PSO-based analysis is done in [19], wherein fast cross-over distributed PSO (FCO DPSO), maximum density convergence DPSO (MDC DPSO), and accurate coverage exploration DPSO (ACE DPSO) models are discussed. These models are applied to tactical applications. It is observed that FCO DPSO showcases faster convergence but has lower distance efficiency when compared with ACE DPSO & MDC DPSO models. The MDC DPSO model has better scalability when compared with ACE DPSO and thus can be used for a wide variety of routing application scenarios. This performance can be improved by using multiple source data capturing models in [20]. This scheme uses multistate unmanned aerial vehicle-borne synthetic aperture radar (SAR) images for depth estimation in UAV path planning scenarios. The model uses Matrix Fourier Transform (MFT) to map images into constrained multiple objective optimization problems (CMOP) to find optimal routing paths. The model has good routing performance but is highly complex and has low scalability when applied to large-scale application scenarios. Further various models extended their feature capturing capabilities of UAV path planning discussed in [21], [22], [23]. The dynamic programming is combined with a heuristic approach (DPHA), direct co-location (DCL) for solar-powered devices, and a QoS-aware heuristic PSO (HPSO) model for device-to-device routing is discussed. These approaches assist in estimating distance, path quality, collision probability, and other features to estimate the most optimum path for a given set of points. Out of these, the HPSO model outperforms other models in terms of path quality but requires a larger computational delay with a greater number of inputs when compared with DPHA & DCL models, thereby limiting its scalability for large-scale application scenarios.

To improve this scalability, work in [24], [25] can be referred to, wherein researchers have combined Game Theory with deep reinforcement learning (GT DRL) and weighted targets sweep coverage (WTSC) to reduce evaluation complexity. Due to this overall delay needed for evaluation is reduced while achieving optimum coverage time and reduced obstacle quality routing path. The GT DRL model is observed to achieve a lower routing cost with lower energy requirements, making it useful for large-scale route evaluation scenarios. But the model doesn't perform well when the number of constraints increases, limiting its usability for practical routing applications, to improve this usability, work in [26], [27] can be referred to wherein bidirectional adaptive A-star model (BIASM) and Voronoi-based Path Generation (VPG) models are discussed. Both these models are capable of considering real-time network constraints, including waypoint coordinates, pitch angles, yaw angles, obstacle radius, and environmental awareness, which assists in obtaining a better path quality compared with smoothed A star (SAS) Soltero models. But these models have higher complexity and require more energy when deployed on real-time networks, limiting their real-time performance. can be improved via the use of bioinspired models for overall optimization, as discussed in [28], wherein multiple objective models are described. These models can capture sensing utility, energy utility, time utility, and risk-utility to generate an optimum route plan for both 2D & 3D environments. The model can combine GA and PSO to improve cumulative utility compared with fixed calculation models.

Some models improve communication quality while path planning improves overall network performance. These models are discussed in [29], [30], [31], wherein average throughput path planning (ATPP), tracking learning detection with kernelized correlation filter (TLD KCF), and dynamic Artificial Potential Field (D-APF) methods are proposed. These methods can reduce redundancies in network communications while maximizing context-specific parameters, including energy efficiency, throughput, and routing speed. The ATPP model has better throughput than TLD KCF, but the latter provides better routing paths when compared with D-APF and ATPP models. The efficiency of these models is limited due to their area of application. The Efficiency can be improved through the models proposed in [32], [33], [34], wherein partially observable Markov decision process (POMDP) with multiple interactive model (IMM), use of multiple agents for reinforcement learning (MAGRL), and flexible path discretization (FPD) are discussed. These models showcase higher communication throughput by lowering redundancies during path planning & routing processes. It is achieved by estimating stochastic routes and then removing them based on performance. Due to this, the MAGRL model outperforms POMDP & FPD models in terms of communication path & travelling route selection but has higher complexity. The POMDP & FPD models showcase moderate route performance but have better computational performance than the MAGRL model, which provides a lot of research scope in both models sets. To reduce this complexity and achieve good routing performance, the work in [35], [36] proposes the use of cooperative path planning (ColPP), & collision-aware Kalman filtering (CAKF), which minimize path planning delays via the removal of temporal collision areas in the path. The CAKF model has high scalability but has moderate routing performance, while the ColPP model is useful for underwater scenarios but has high throughput with low latency. The performance of these models must be tested on multiple scenarios to validate their scalability. This performance can be optimized via the use of bioinspired models like multiple objective PSO with image & terrain data (MOPSO ITD) [37], and adaptive Grey wolf optimization (AGWO) [38], wherein multiple inputs are used to reduce error rate, and optimize routing path quality. The model is observed to be superior to a non-domination-based genetic algorithm for multiple objective optimizations (NSGA), MOPSO, GWO, and Nonlinear GWO (NGWO), logarithmic GWO (LGWO), and MFO models when applied to the same terrain simulation conditions.

A high-cost, high-efficiency model for joint detection & tracking of radio-tagged objects is discussed in [39], wherein multiple routing nodes are combined to identify the target location. The model uses a partially observable Markov decision process (POMDP) to perform this task with low delay and low error probability while tracing different-sized objects. It is primarily used for object tracking but can be extended for path planning with different algorithmic constraints. The efficiency of this model is further improved via the work in [40], wherein Meteorology aware path planning with Improved Intelligent Water Drops model (IIWDM) is discussed. The model reduces average flight time and collision risk and improves flight speed through replanning and force effect evaluation as observed and performs better compared with ACO, GA, and Q-learning models on the same dataset. Similar models are proposed in [41], [42], [43]. The researchers have explored use-cases of multiple objective path planning via online and offline search (MOPP, OFONSA), improved bias reduction pseudo-linear estimator (IBRPLE), and software-defined network (SDN) approach for path planning is described. These approaches assist in reducing dependency on a single controller for path planning via software-based patches, which have run-time reconfiguration capabilities. The SDN model outperforms other models in terms of flexibility and control efficiency but has lower throughput when compared with MOPP, OFONSA and IBPRLE models due to multiple layered architectures. This performance can be further improved by mixing strategy based Gravitational search algorithm (MSGSA) [44]. The channel-aware potential field trajectory planning [45], estimation of distribution algorithm (EDA) with the genetic algorithm (GA) [46]. Discrete Pigeon-inspired Optimization (DPO) [47] models, which achieve better throughput via temporal analysis of path parameters, thereby incrementally tuning their internal performance. These models can improve route selection performance by identifying paths with a minimum number of collisions and maximum safe areas. The energy needed for routing is optimized, which internally optimizes the lifetime of UAV nodes. These models are generic and can be used for multiple terrain and traffic types with moderate performance. To improve performance for application-specific UAV routing scenarios, in [48], [49], [50] propose 3D Mountain terrain-based cooperative combat planning. This scheme uses life-cycle Swarm Optimization (LSO), hybrid PSO with Gauss pseudo-spectral method (HPSO GPM), and reliable path planning (RPP) is proposed. These models provide solutions for context-specific scenarios, thereby assisting in achieving high throughput with low overheads. It can be observed that a wide variety of models are proposed for path planning in UAV traffic conditions, which vary in terms of complexity, area of deployment, and other metrics. An evaluation of these algorithms in terms of computational delay, routing delay, deployment complexity, energy efficiency, and area of application can be observed in the next section. This will assist readers in identifying the best system models suited for a particular type of UAV path planning application scenario.

3. Statistical analysis

From the detailed review, it can be observed that UAV routing models have highly variant performance in terms of scalability, area of application, etc. To identify the best performing models, they were compared in terms of statistical parameters, which include computational delay (CD), routing delay (RD), deployment complexity (CC), energy efficiency (EE), and area of application (AA). The reviewed models were tested on different deployment scenarios; thus, absolute values of these parameters were not available. To compare these models, their parameters were converted into fuzzy ranges of Low (L=2), Medium (M=3), High (H=4), and Very High (VH=5), depending upon their internal implementations. For instance, the delay needed by MOPP OFONSA [41] model is very high compared to DCL [22], based on which the table showcases different performance levels for other models. Table 1 showcases this comparison for each model, allowing researchers to identify the best-performing method per their network requirements.

From this review, it can be observed that MVO CPS [10], IASA [13], PID [14], FCO DPSO [15], DCL [18], VPG [23], and SDN [39] have the lowest convergence delay, while Schur Compliment [11], MGPO [12], ANN SPSO AS [14], MDC DPSO [15], ACE DPSO [15], GT DRL [20], ATPP [25], MAGRL [29], POMDP [35], MOPP OFONSA [37], MSGSA [40], and RPP [46] provide the fastest route between any two UAV accessible points. Thus, these models must be used for low delay and high throughput applications. Similarly, computational complexity of K-Means [4], ILP [4], PID [14], MDC DPSO [15], WTSC [21], VPG [23], and FPD [30] is the lowest, while, energy

TABLE I. Statistical evaluation of the reviewed models

Method & Year	CD	RD	CC	EE	AA
MPM [6] - (2016)	4	3	4	2	General
GAR [7] - (2021)	4	4	3	2	General
AODV [7] - (2021)	3	5	3	2	General
DSR [7] - (2021)	3	5	3	2	General
GA ILP [8] - (2011)	5	3	4	3	General
K-Means [8] - (2011)	3	5	2	2	General
ILP [8] - (2011)	3	5	2	2	General
SIMST [9] - (2018)	4	3	3	4	General
MOU AV [11] - (2020)	3	3	3	4	General
BI SS ANN [12] - (2021)	4	3	5	3	General
ABC [12] - (2021)	4	4	4	3	General
DA [12] - (2021)	4	4	4	2	General
SIFT SVM [13] - (2019)	4	3	5	2	Image based
MVO CPS [14] - (2018)	2	3	4	3	General
ALO [14] - (2018)	4	4	3	3	General
MFO [14] - (2018)	3	4	3	3	General
WOM [14] - (2018)	3	4	4	3	General
GWO [14] - (2018)	4	3	3	3	General
Schur Compliment [15] - (2019)	3	2	4	3	General
MGPO [16] - (2020)	3	2	3	4	General
IASA [17] - (2020)	2	3	4	3	General
AS [17] - (2020)	3	4	4	3	General
DS [17] - (2020)	4	3	4	3	General
ANN SPSO AS [18] - (2019)	3	2	3	3	General
PID [18] - (2019)	2	4	2	2	General
Fuzzy [19] - (2019)	3	4	3	3	General
PSO Swap [18] - (2019)	4	3	4	3	General
SPSO with chaotic inertia weight [18] - (2019)	4	4	3	3	General
SPSO with adaptive weighing measures [18] - (2019)	4	4	4	3	General
FCO DPSO [19] - (2019)	2	3	3	2	General
MDC DPSO [19] - (2019)	3	2	2	3	General
ACE DPSO [19] - (2019)	3	2	3	4	General
MFT CMOP [20] - (2021)	4	3	5	2	Image based
DPHA [21] - (2020)	3	3	4	3	General
DCL [22] - (2020)	2	4	3	4	Solar power devices
HPSO [23] - (2020)	4	3	4	3	General
GT DRL [24] - (2019)	4	2	4	3	General
WTSC [25] - (2020)	3	3	2	3	General
BIASM [26] - (2020)	3	3	3	2	General
VPG [27] - (2020)	2	3	2	3	General
GA & PSO [28] - (2018)	4	3	5	3	General
ATPP [29] - (2019)	3	2	3	2	General
TLD KCF [30] - (2018)	3	3	4	3	General
D-APF [31] - (2020)	4	3	3	3	General
POMPDP IMM [32] - (2019)	3	3	4	3	General
MAGRL [33] - (2019)	5	2	4	3	General
FPD [34] - (2021)	3	3	2	2	General
CoIPP [35] - (2020)	3	4	3	3	Under-water
CAKF [36] - (2018)	3	3	4	3	General
MOPSO ITD [37] - (2020)	4	3	5	3	Image based
AGWO [38] - (2021)	3	3	4	3	General

Method & Year	CD	RD	CC	EE	AA
NSGA [38] - (2021)	4	3	3	3	General
MOPSO [38] - (2021)	4	4	3	3	General
GWO [38] - (2021)	4	3	3	2	General
NGWO [38] - (2021)	4	3	4	3	General
LGWO [38] - (2021)	3	4	3	3	General
MFO [38] - (2021)	3	3	4	2	General
POMDP [39] - (2019)	4	2	5	3	General
IIWDM [40] - (2021)	3	3	4	3	General
ACO [40] - (2021)	4	3	4	3	General
GA [40] - (2021)	3	4	3	3	General
QL [40] - (2021)	4	3	4	2	General
MOPP OFONSA [41] - (2017)	5	2	3	3	General
IBRPLE [42] - (2019)	4	3	3	3	General
SDN [43] - (2020)	2	3	4	3	General
MSGSA [44] - (2021)	4	2	4	3	General
EDA GA [46] - (2020)	3	3	4	4	General
DPO [47] - (2020)	4	3	4	3	General
LSO [48] - (2020)	3	3	3	4	Terrain based applns.
HPSO GPM [49] - (2021)	4	3	4	2	General
RPP [50] - (2020)	4	2	3	3	General

efficiency of SIMST [5], MOU AV [7], MGPO [12], ACE DPSO [15], DCL [18], EDA GA [42], and LSO [44] is the highest, which makes these models useful for low energy applications. A parametric evaluation is depicted in Figure 5. But this comparison is highly parameter specific, which can be improved if the compared parameters are fused. To perform this task, a novel algorithmic rank score (ARS) is developed, which can be seen through equation 3 as follows,

$$ARS = \frac{4}{CD} + \frac{4}{RD} + \frac{4}{CC} + \frac{EE}{4} \ldots \tag{3}$$

suited for a particular type of UAV path planning application scenario. In this equation, CD, RD & CC must be low for a model to be classified as good, while EE must be high, due to which CC, RD & CC are in denominator while EE is in numerator while analysis.Based on this evaluation, the algorithmic rank is calculated, and its values are tabulated in table 2 as follows,

From the evaluation in table 2, it can be observed that MDC DPSO [15], VPG [23], MGPO [12], ACE DPSO [15], PID [14], ANN SPSO AS [14], and WTSC [21] have better overall performance, and thus can be used for high efficiency, and low delay UAV routing applications.

4. Description of model

It can be observed that a wide variety of models are available for low-cost, and high-efficiency UAV routing & path planning, which assists in the selection of high-efficiency methods that showcase low delay, low energy, and better routing performance. These models utilize deep learning-based methods, which stochastically determine multiple routing paths and identify fitness functions for improving path selection efficiency. Each of these models also uses path augmentation, which reduces errors, and improves the overall efficiency of the route deployment process. These models can be deployed for large-scale networks, which makes them highly useful and scalable.

5. Conclusion

This text reviews various models for path planning in UAV scenarios. Each model is evaluated in terms of computational delay, routing delay, computational complexity, and energy efficiency. This comparison shows that models with lower computational delay often result in moderate to high delay paths, while models with low complexity result in better energy efficiency. Based on this comparison, it is observed that MVO CPS, IASA, PID, FCO DPSO, DCL, VPG, and SDN are used to quickly obtain approximate UAV routes, making them useful for low-delay UAV networks. But these models do not provide the most optimum routes due to their coarse-level analysis. To obtain routes that can reduce UAV travel delays, Schur Complement, MGPO, ANN SPSO AS, MDC DPSO, ACE DPSO, GT DRL, ATPP, MAGRL, POMDP, MOPP OFONSA, MSGSA, and RPP models must be used. These models reduce redundancies during path planning and allow low-distance paths with a minimum probability of UAV-to-UAV collision. If the network requires low energy consumption, then SIMST, MOU AV, MGPO, ACE DPSO, DCL, EDA GA, and LSO models are preferred, which aim at providing paths that require minimum transportation energy, thereby improving the overall network lifetime. The performance of these models was fused, and a novel algorithmic rank score was evaluated, which indicates that MDC DPSO, VPG, MGPO, ACE DPSO, PID, ANN SPSO AS, and WTSC have lower convergence delay, lower routing delay, lower complexity, and better energy efficiency when compared with other UAV

TABLE II. ARS for different models

Method	ARS	Rank
MDC DPSO [19]	6.08	1
VPG [27]	6.08	2
MGPO [16]	5.67	3
ACE DPSO [19]	5.67	4
PID [18]	5.50	5
ANN SPSO AS [18]	5.42	6
WTSC [25]	5.42	7
DCL [22]	5.33	8
FCO DPSO [19]	5.17	9
ATPP [29]	5.17	10
FPD [34]	5.17	11
MVO CPS [14]	5.08	12
Schur Compliment [15]	5.08	13
IASA [17]	5.08	14
SDN [43]	5.08	15
RPP [50]	5.08	16
MOU AV [11]	5.00	17
LSO [48]	5.00	18
MOPP OFONSA [41]	4.88	19
GT DRL [24]	4.75	20
MSGSA [44]	4.75	21
SIMST [9]	4.67	22
EDA GA [46]	4.67	23
K-Means [8]	4.63	24
ILP [8]	4.63	25
MAGRL [33]	4.55	26
POMDP [39]	4.55	27
BIASM [26]	4.50	28
MFO [14]	4.42	29
GWO [14]	4.42	30
Fuzzy [19]	4.42	31
DPHA [21]	4.42	32
TLD KCF [30]	4.42	33
D-APF [31]	4.42	34
POMPDP IMM [32]	4.42	35
CoIPP [35]	4.42	36
CAKF [36]	4.42	37
AGWO [38]	4.42	38
NSGA [38]	4.42	39
LGWO [38]	4.42	40
IIWDM [40]	4.42	41
GA [40]	4.42	42
IBRPLE [42]	4.42	43
GWO [38]	4.17	44
MFO [38]	4.17	45
ALO [14]	4.08	46
WOM [14]	4.08	47
AS [17]	4.08	48
DS [17]	4.08	49
PSO Swap [18]	4.08	50
SPSO with chaotic inertia weight [18]	4.08	51
HPSO [23]	4.08	52
MOPSO [38]	4.08	53

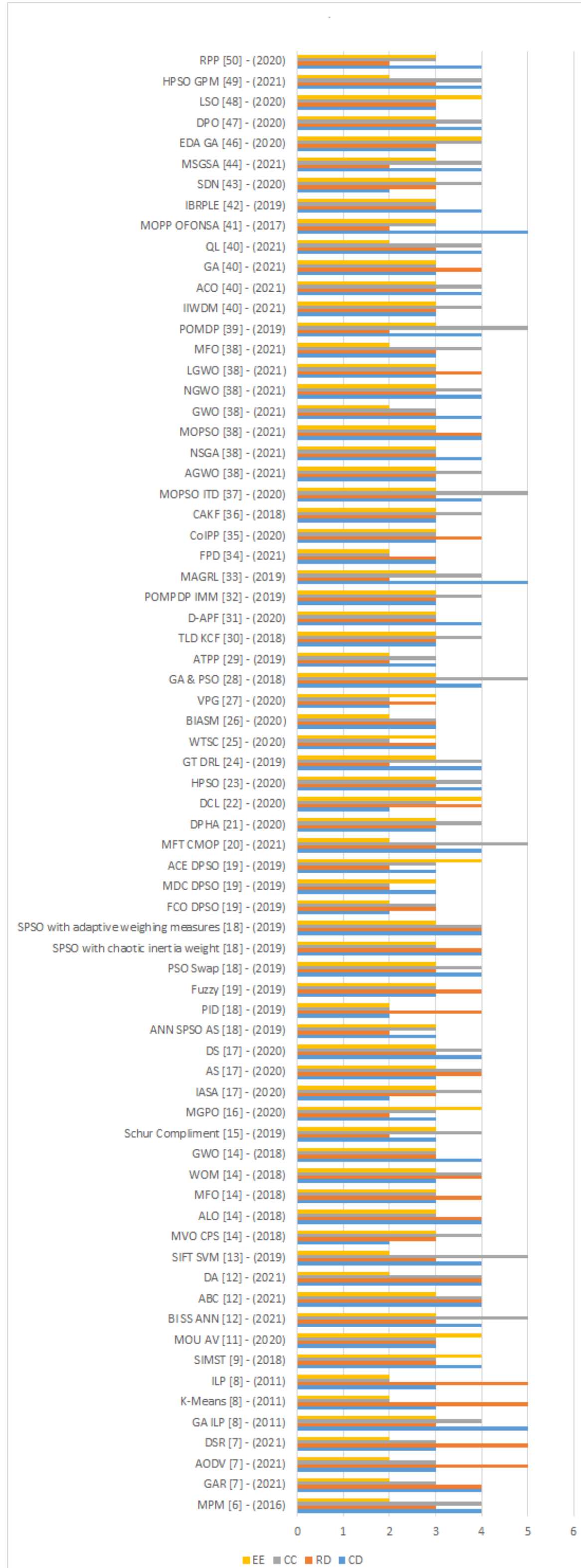

Figure 5. Parametric comparison of reviewed models

Method	ARS	Rank
NGWO [38]	4.08	54
ACO [40]	4.08	55
DPO [47]	4.08	56
AODV [7]	3.97	57
DSR [7]	3.97	58
GA ILP [8]	3.88	59
BI SS ANN [12]	3.88	60
GA & PSO [28]	3.88	61
MOPSO ITD [37]	3.88	62
MPM [6]	3.83	63
GAR [7]	3.83	64
QL [40]	3.83	65
HPSO GPM [49]	3.83	66
ABC [12]	3.75	67
DA [12]	3.50	71

path planning models. Thus, these models must be deployed in real-time UAV network application scenarios for overall performance enhancement. In the future, researchers can combine these models to obtain fused methods that have lower energy consumption and faster travel speed. It can be achieved by ensembling multiple algorithms and selecting them via Q-learning or bioinspired network optimization models. Such ensemble models will further improve network scalability and make the UAV model applicable for various application efficiencies.

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