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Research Article

Energy-Efficient Hybrid Bio-Inspired Approach for Low-Latency Collision-Aware UAV Networks

Anshu Vashisth[1], Gagandeep Kaur[2*], Bhupinder Kaur[3], Kartikey Jaiswal[4]

[1]*School of Computer Science and Engineering, Lovely Professional University, Jalandhar, Punjab, India. anshu.parents@gmail.com*

[2]*School of Computer Science and Engineering, Lovely Professional University, Jalandhar, Punjab, India. gagan.dhoofer@gmail.com*

[3]*School of Computer Science and Engineering, Lovely Professional University, Jalandhar, Punjab, India. bhupinder.kaur.bhatia786@gmail.com*

[4]*School of Computer Science and Engineering, Lovely Professional University, Jalandhar, Punjab, India. karan74jaiswal@gmail.com*

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ABSTRACT

The pervasive integration of Unmanned Aerial Vehicle (UAV) networks across various applications underscores the imperative for sophisticated communication and collision avoidance strategies to optimize their operational prowess. Traditional UAV network optimization methodologies grapple with inherent challenges related to collision minimization and channel utilization, resulting in detrimental outcomes such as elevated communication delays, increased energy consumption, and compromised throughput alongside diminished packet delivery ratios. This study addresses these shortcomings through the introduction of an innovative optimization model that synergizes the robust characteristics of the Teacher Learner-based Grey Wolf Optimizer (TLGWO) and the Bat Firefly Optimizer (BFFO), thereby significantly elevating the overall performance of UAV networks. The TLGWO component of the pro-posed model is intricately designed to minimize collisions among UAV nodes by analytically assessing temporal and spatial performance metrics. This includes a nuanced examination of communication delay dynamics and the historical context of avoided collisions. Simultaneously, the BFFO module is engineered to maximize channel utilization, leveraging the same performance metrics for a holistic optimization approach. The dual application of TLGWO and BFFO ensures a comprehensive enhancement of UAV network efficiency. Empirical validation demonstrates the superiority of the proposed model over existing methods, showcasing a remarkable 10.4% reduction in communication delay, an 8.5% improvement in energy efficiency, a 3.5% increase in packet delivery ratio, a 9.5% enhancement in throughput, and a 4.9% reduction in collision occurrences. The significant impact of this research is far-reaching, providing a robust and versatile framework for fortifying UAV network efficiency across diverse applications, thereby propelling the field towards more dependable and efficient UAV deployments in critical sectors.

Keywords: Unmanned Aerial Vehicles, Collision, Channel Utilization, Grey Wolf Optimizer, Firefly Algorithm, Packet Delivery and Latency.

INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have changed a number of industries, including precision agriculture, dis-aster relief, military surveillance, and next-generation communication networks. The need for low-latency, collision-aware, and energy-efficient optimization techniques has increased with the proliferation of UAV networks. Managing UAV networks has many difficulties, especially when it comes to maintaining smooth communication, lowering the chance of collisions, and optimizing channel us-age in extremely dynamic and dispersed environments. Conventional UAV network optimization techniques have frequently given priority to either communication efficiency or collision avoidance, failing to comprehensively in-corporate both goals. The scalability and dependability of UAV networks in complicated scenarios are eventually limited by this fragmented approach, which causes increased communication delays, excessive energy consumption, de-creased throughput, and lower packet delivery ratios. This study suggests an Energy-Efficient Hybrid Bio-Inspired Approach that combines Bat Firefly Optimizer (BFFO) and Teacher Learner-based Grey Wolf Optimizer (TLGWO) to solve these important issues, providing a thorough and

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complementary solution. By analysing geographical and temporal performance parameters, the TLGWO component effectively reduces communication delays and improves UAV coordination, hence mitigating collisions. The BFFO module simultaneously concentrates on optimizing channel utilization, guaranteeing increased network speed and data transmission dependability. Our suggested model provides a balanced trade-off between collision minimization and network efficiency by utilizing the advantages of both nature-inspired algorithms, which represents a significant development in UAV network optimization. The superiority of this hybrid bio-inspired model is demonstrated by experimental validation, which shows notable gains in several important performance metrics, such as increased energy efficiency, decreased packet delivery ratio, enhanced throughput, decreased communication time, and fewer UAV collisions. In addition to its technological contributions, this study creates a framework for managing UAV networks that is both scalable and adaptable, enabling their dependable deployment in situations that are crucial to mission success. The results of this study set a new standard for low-latency, collision-aware, and energy-efficient UAV operations, opening the door for next-generation UAV networks. In this paper, Section 1 provides a brief introduction to the research problem, outlining the motivation behind this study. Section 2 presents a comprehensive review of existing work in the field, highlighting key advancements and research gaps. Section 3 details the working of the pro-posed hybrid bio-inspired optimization model, explaining its components and implementation. Section 4 showcases the experimental results and performance analysis, demonstrating the effectiveness of the proposed approach. Finally, Section 5 discusses the future scope of this research and concludes the study, summarizing key findings and potential advancements in UAV network optimization.

MOTIVATION

Unmanned aerial vehicles (UAVs) are being used in a wider range of applications, which calls for low-latency and energy-efficient communication techniques that guarantee collision avoidance in dynamic airspace. Conventional UAV network optimization methods frequently handle channel utilization and collision minimization independently, which results in wasteful energy use, longer communication latency, and worse network dependability. The smooth operation of UAV networks in mission-critical contexts is hampered by the absence of a comprehensive strategy that simultaneously improves collision avoidance and maximizes communication efficiency. By combining the Bat Firefly Optimizer and the Teacher Learner-based Grey Wolf Optimizer, this study suggests an Energy-Efficient Hybrid Bio-Inspired Optimization Model to address these issues. By reducing collisions, increasing channel utilization, and improving network performance all at once, this strategy seeks to create a low-latency, energy-efficient UAV network that can manage demanding aerial operations. As UAVs continue to play an increasing role in applications like precision agriculture, surveillance, and disaster response, it is imperative that UAV networks be optimized to provide energy-efficient, low-latency, and collision-aware operations. Conventional optimization methods frequently focus only on communication efficiency or collision avoidance, which results in less-than-ideal network performance marked by higher energy consumption, longer communication delays, and worse reliability. To get over these restrictions, however, this study presents a novel hybrid bio-inspired optimization model that smoothly combines the Bat Firefly Optimizer (BFFO) and Teacher Learner-based Grey Wolf Optimizer (TLGWO). By optimizing spatial and temporal performance parameters, the TLGWO component aims to minimize UAV collisions, im-proving network safety and lowering the chance of in-air accidents. The BFFO module is made to maximize channel use at the same time, guaranteeing increased throughput, better packet delivery ratios, and more effective data trans-fer. The suggested model sets a new standard for UAV network optimization by combining these two sophisticated nature-inspired algorithms to provide a comprehensive solution that improves collision avoidance and maximizes network efficiency. The outcome shows how effective this hybrid strategy is, with significant gains in several important performance parameters, such as decreased communication latency, higher energy economy, improved packet delivery ratio, and fewer collisions. This model's wide applicability makes it very useful for a variety of UAV-driven industries, allowing for more dependable and scalable UAV deployments in environments that are crucial to mission success. In addition to addressing urgent issues in UAV network optimization, this study but also creates a revolutionary architecture that guarantees low-latency and energy-efficient UAV operations. This study advances UAV technology by bridging the gap between collision awareness and communication efficiency, providing a complete and scalable solution for next-generation UAV networks.

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RELATED WORK

BPACAR, a bio-inspired model for dynamic collision-aware routing in UAV networks, was proposed by Vashisth et al. [1]. This model efficiently reduces UAV collisions while maximizing network performance by utilizing continuous pattern analysis. In order to lower the risk of mid-air accidents, the study presented an adaptive learning framework that modifies UAV movement tactics in response to real-time data. The model performed better than traditional routing methods in tests conducted in a variety of mobility settings. QMRNB, a Q-learning-based model that uses bio-inspired optimization strategies to in-crease routing efficiency in UAV networks, was presented by Vashisth et al. [2]. In order to improve UAV coordination and network throughput, this study concentrated on combining reinforcement learning with models inspired by nature. The suggested method ensures effective energy use by dynamically modifying route choices based on historical data. It is a feasible option for real-time UAV ap-plications, since performance assessments showed de-creased communication latency and enhanced packet delivery ratios. Additionally, a systematic review of current UAV path-planning methods was carried out by Vashisth et al. [3]. This study emphasized the need for more adaptable models by classifying different approaches and pointing out the drawbacks of traditional methods. The authors identified important research gaps by analysing deterministic, heuristic, and AI-based path planning techniques. The review emphasized how crucial multi-objective optimization is for UAV navigation, especially in settings with limited energy. An overview of UAV communication networks was given by Vashisth and Batth [4], who also covered the main issues with collision avoidance, energy efficiency, and routing. Ad hoc and cellular-based UAV networks were among the several networking paradigms examined in the study. The results showed serious flaws in the current routing methods, especially with regard to scalability and latency. To im-prove UAV networking efficiency, the authors suggested a hybrid communication system that makes use of several connectivity options. Their further research [10] further established edge computing's place in next-generation UAV networks by examining its classification, uses, and difficulties. The study proposed a unique architecture for integrating UAVs with edge computing frameworks and investigated the effects of edge computing on energy efficiency and latency reduction. Results showed that mission-critical UAV applications saw notable performance gains. A multi-agent reinforcement learning framework for UAV swarm routing was presented by Wang et al. [12], which enhanced decision-making under changing circum-stances. A decentralized control system that allows UAVs to automatically learn and adjust to changing situations was provided in the study. The outcomes of the experiment demonstrated increased swarm coordination, decreased energy usage, and greater routing efficiency. For UAV networks, Garg et al. [13] created a congestion-aware routing system that maximizes communication effectiveness in situations with high mobility. The protocol ensures dependable data transfer by dynamically modifying routing paths in response to network congestion conditions. Its efficacy in reducing communication bottlenecks in UAV-based communication networks was shown by simulations. For smart city UAV communications, Wei et al. [14] suggested a low-delay routing strategy that guarantees re-al-time data transfer. An adaptive routing method that gives priority to latency-sensitive applications was introduced in the study. Tested in urban settings, the suggested method showed faster emergency communication network response times. In order to improve communication reliability, Guo et al. [15] presented an intelligent clustering routing technique for UAV ad hoc networks. A clustering-based routing system that improves network scalability and lowers energy consumption was suggested by the study. The results demonstrated increased UAV operating time and enhanced network stability. Other research, such as those by Zhang et al. [17], Liu et al. [18], Beegum et al. [16], and Mansoor et al. [19], looked at Q-learning-based routing, privacy-preserving UAV communication, bio-inspired optimization, and a thorough analysis of UAV routing proto-cols, respectively. Together, these efforts progress the development of scalable, secure, and energy-efficient UAV networks. In recent research, connectivity-aware path planning, urban mobility integration, and energy optimization in UAV-IoT networks have been studied by Gangopadhyay and Jain [20], Bashir et al. [21], and Yeduri et al. [22]. These experiments demonstrate how crucial real-time adaptive routing techniques are becoming for UAV networks. Fan et al. [23], Kumbhar and Shin [24], and Rezaee et al. [25] have also investigated deep reinforcement learning and multi-objective optimization, introducing intelligent UAV routing frameworks for dynamic environments. Khayat et al. [27] and Shnaiwer et al. [26] concentrated on laten-cy-aware clustering methods and Multihop task routing. et al. [33] and Zhou et al. [34] investigated decentralized UAV exploration frameworks, intelligent transportation integration, and secure UAV networking. The creation of reliable, scalable,

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and resilient UAV deployments is aided by these studies. Table 1 below is a summary table containing the methodology used, algorithm used, advantages, and disadvantages for each reference from your related work section.

Reference	Methodology Used	Algorithm Used	Advantages	Disadvantages
[1] Vashisth et al.	Bio-inspired optimization for collision-aware UAV routing	BPACAR (Bio-inspired)	Improves collision avoidance and network efficiency	Requires high computational resources
[2] Vashisth et al.	Q-learning based optimization for UAV routing	QMRNB (Q-learning)	Enhances routing efficiency and network adaptability	May face challenges in highly dynamic environments
[12] Wang et al.	Multi-agent reinforcement learning for UAV swarm routing	Reinforcement learning	Improves UAV swarm decision-making in real-time	Needs extensive training data for effective learning
[13] Garg et al.	Congestion-aware dynamic routing for high-mobility UAVs	Adaptive congestion-aware routing	Reduces congestion and optimizes UAV mobility	May struggle with sudden UAV mobility changes
[14] Wei et al.	Low-delay routing for real-time smart city UAV communications	Adaptive low-latency routing	Ensures real-time data transmission in urban UAV networks	Limited scalability in highly dynamic urban settings
[16] Beegum et al.	Bio-inspired optimization techniques for FANETs	Particle Swarm Optimization, Ant Colony Optimization	Optimizes UAV swarm network efficiency	May not adapt well to real-world UAV deployment scenarios
[17] Zhang et al.	Q-learning based intelligent routing for UAV networks	Q-learning	Improves UAV network performance using Q-learning	Requires extensive learning phase for optimal results
[18] Liu et al.	Privacy-preserving decentralized UAV communication	Decentralized encryption-based protocols	Ensures secure UAV communication against cyber threats	Encryption-based methods may introduce processing delays
[22] Yeduri et al.	Energy-efficient optimization for UAV-IoT networks	Energy-aware routing	Reduces energy consumption in UAV-IoT applications	Energy optimization trade-offs may impact performance
[33] Zhai et al.	Secure UAV networking and attack detection	AI-enhanced security protocols	Enhances UAV cybersecurity resilience	Security solutions can add communication overhead

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PROPOSED MODEL

As per the review of existing models used for enhancing the efficiency of UAV Networks, it can be observed that most of these models either have higher complexity or have lower efficiency when deployed for large-scale networks. To overcome these issues, this section discusses the design of an efficient fusion of Teacher Learner-Based Grey Wolf and Bat Firefly Optimizers, each of which aims at optimizing an intricate aspect of the UAV routing process. As per Figures 1 and 1.1, it has been seen that the Grey Wolf Optimizer (GWO) and Bat Firefly Optimizer (BFO) are combined in UTGBO to improve UAV network efficiency levels. UTGBO uses advanced optimization techniques to minimize collisions and maximize channel utilization, considering communication delay and collision avoidance. This dual-approach optimization model reduces delay, boosts energy efficiency, and boosts packet delivery ratios while scaling across UAV routing scenarios. UTGBO's contributions will improve UAV network performance, enabling more reliable and effective critical sector deployments. Figure 1 depicting the overall flow of the proposed model for enhancing the routing efficiency of UAV Networks. In this process, the TLGWO component is specifically de-signed for minimizing collisions among UAV nodes by effectively analyzing temporal and spatial performance metrics, including communication delay and previously avoided collisions. To perform this task, the proposed model initially estimates an iterative UAV Node Rank (UNR) via equation 1,

$$UNR = \frac{1}{NR}\sum_{i=1}^{NR}\frac{THR(i) * PDR(i)}{D(i) * NAC(i)} \dots (1)$$

Where THR represents the throughput observed during communications & is estimated via equation 2, PDR represents the Packet Delivery Ratio during communications & is calculated via equation 3, D is the delay needed which is estimated via equation 4, while NAC is the Number of Active Collisions during previous NR routing requests.

$$THR = \frac{N(P(rx))}{N(P(tx))} \dots (2)$$

Where N(P(rx)) & N(P(tx)) represent the number of packets received & transmitted during routing communications.

$$PDR = \frac{N\big(P(rx)\big)}{D} \dots (3)$$

$$D = ts(tx) - ts(rx) \dots (4)$$

Where ts(tx) & ts(rx)represents the timestamps of transmission & reception instance sets. Using this node rank, the TLGWO model initially generates NP particles for each routing request via equation 5

$$N = STOCH(2, NN(Sel)) \dots (5)$$

Where, N represents several nodes through which the UAV routing will take place, while NN(Sel) represents the total number of selected nodes, which are the number of nodes between source & destination nodes. Based on these selected nodes, the model estimates Particle Fitness via equation 6,

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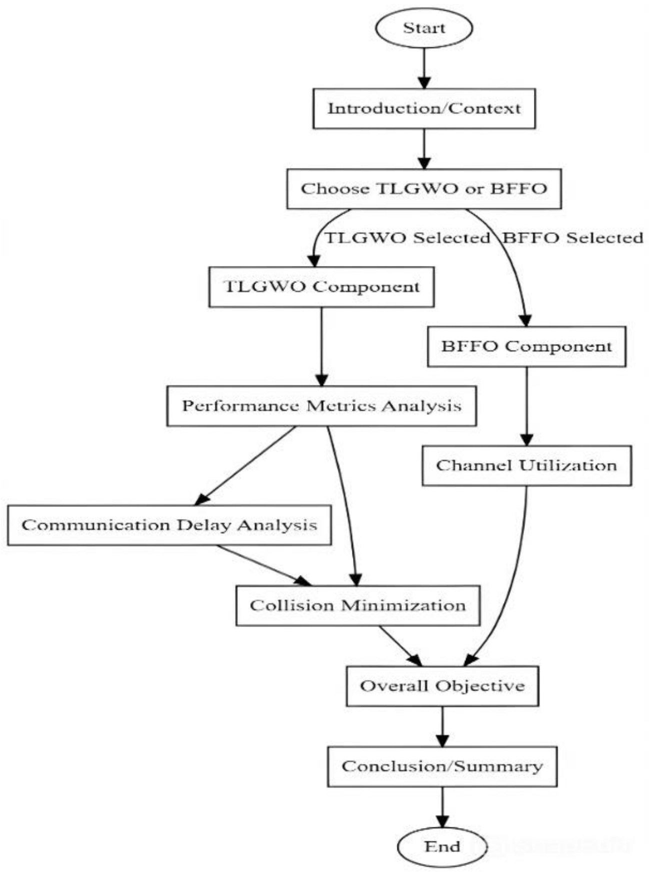

Figure 1. The overall flow of the proposed model for enhancing the routing efficiency of UAV Networks

$$PF = \frac{1}{N^2}\sum_{i=1}^{N} UNR(i) * E(i) \sum_{j=1}^{N} \frac{UNR(j)}{d(i,j)} \dots (6)$$

Where, E represents the residual energy of the node, while d(i,j)represents the distance between the nodes. After estimating the fitness for NP particles, the model evaluates the fitness threshold via equation 7,

$$fth = \frac{\sum_{i=1}^{NP} PF(i) * LR}{NP} \dots (7)$$

Where LR is the rate at which particles learn from other particles. Based on this evaluation, the model marks particles as 'Teachers if PF>2*fth, while the remaining particles are marked as 'Students', and are updated using GWO optimizations. Out of these particles, students with PF>fth are marked as 'Alpha' Wolves and their configuration is updated via equation 8,

$$N(Alpha) = STOCH\big(N(Teacher)\big) \bigcup STOCH\big(N(Alpha)\big) \dots (8)$$

This evaluation assists in replacing nodes in Alpha Wolves Stochastically with nodes from Teacher Particles. Similarly, Particles with PF<3*fth are marked as ‘Delta’, and their configuration is updated via equation 9,

$$N(Delta) = STOCH\big(N(Gamma)\big) \bigcup STOCH\big(N(Delta)\big) \dots (9)$$

While Particles with PF<2*fth are marked as ‘Gamma’, and their routing configuration is updated via equation 10,

$$N(Gamma) = STOCH\big(N(Beta)\big) \bigcup STOCH\big(N(Gamma)\big) \dots (10)$$

The remaining particles are marked as 'Beta', and their con-figuration is updated via equation 11,

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$$N(Beta) = STOCH\big(N(Alpha)\big) \bigcup STOCH\big(N(Beta)\big) \dots (11)$$

This process is repeated for NI Iteration Sets, and the particle with the highest fitness is selected for routing between UAV Nodes. Similar to TLGWO, the model also deploys BFFO, which focuses on maximizing channel utilization, taking into account the same performance metrics. The BFFO Model Initially Generates NB Bats, where each Bat consists of the node's channel utilization (CU), this is via equation 12,

$$CU = STOCH(0,1) \dots (12)$$

Based on this channel utilization percentage, nodes selected from the TLGWO process perform communications on the network, based on which Bat Fitness is estimated via equation 13,

$$BF = \frac{1}{N(TLGWO)} \sum_{i=1}^{N(TLGWO)} \frac{THR(i) * PDR(i)}{D(i) * e(i)} \dots (13)$$

Where e represents the energy consumed during communications. After estimating Bat Fitness for all Bats, the model calculates the Bat Fitness Threshold via equation 14,

$$BF(th) = \frac{1}{NB} \sum_{i=1}^{NB} BF(i) * LR \dots (14)$$

Bats with BF>BF (th)are passed to the Next Iteration, while other Bats are marked as 'Fireflies', and their brightness corresponds to bat fitness. Fireflies with a brightness higher than BF (th)*LR are attracted to each other, while others are discarded from the communication process. Channel Utilization of Fireflies that are attracted towards each other is updated via equation 15,

$$CU(New) = \frac{CU(Old) + CU(Max(BF))}{2} \dots (15)$$

Where CU (Max (BF)) represents channel utilization of Firefly with maximum fitness levels. This process is repeated for NI Iteration Sets, and at the end of the final iteration Bat with maximum fitness is identified, and its channel utilization is used by individual nodes. Based on these integrated operations, the model can reduce collisions and improve channel utilization levels. The efficiency of this model was estimated for different scenarios and compared with existing models in the next section of this text.

By tackling collision avoidance and channel optimization simultaneously, which traditional models frequently manage separately, the proposed UTGBO model aims to improve the efficiency of UAV networks. The Bat Firefly Optimizer (BFFO) dynamically optimizes communication channels for effective data transmission, while the Teacher Learner-Based Grey Wolf Optimizer (TLGWO) is integrated to control UAV movement and avoid collisions. In contrast to traditional optimization models, which concentrate on either communication efficiency or collision reduction, UTGBO successfully strikes a compromise between the two, guaranteeing seamless UAV operations in extremely dynamic environments. With the help of TLGWO's teacher-learner mechanism, UAVs can gradually improve their collision avoidance skills by learning from their prior choices. It is more successful than current models like Q-Learning, Deep Reinforcement Learning, and Multi-Agent Reinforcement Learning because of this adaptive learning strategy, which depends on predetermined training as opposed to making decisions in real time. Furthermore, by dynamically modifying channel assignments, BFFO improves network performance by guaranteeing ideal data transfer and low interference. When applied separately, traditional Firefly and Bat algorithms can suffer from either excessive exploration or underutilization of network resources. UTGBO guarantees a reliable and effective UAV network that can manage extensive deployments by integrating these bio-inspired strategies. Applications like real-time monitoring, disaster management, and autonomous drone fleets benefit greatly from the hybrid approach's reduced communication latency, increased energy economy, improved packet delivery, and increased throughput. Additionally, UTGBO is very scalable, which makes it ideal for intricate UAV networks where responsiveness, flexibility, and dependability are essential. This methodology establishes a new standard for optimizing UAV networks. The study introduces UTGBO, a unique hybrid bio-inspired optimization model that tackles the problems of collision avoidance and channel optimization to increase the efficiency of UAV networks. It

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combines Bat Firefly Optimizer (BFFO) to maximize channel utilization and Teacher Learner-Based Grey Wolf Optimizer (TLGWO) to improve UAV coordination, guaranteeing a balanced trade-off between safety and communication effectiveness. In contrast to traditional models that focus on either network performance or collision reduction, UTGBO effectively integrates the two, leading to increased data transmission, reduced communication delays, and improved energy consumption. The adaptive learning process introduced by the teacher-learner mechanism in TLGWO improves UAVs' ability to avoid collisions in midair, whereas BFFO dynamically distributes channels to optimize network throughput. The study offers a comparison with current optimization models like Q-Learning, Multi-Agent Reinforcement Learning and Deep Reinforcement Learning have shown notable performance gains in a variety of UAV routing scenarios.

RESULT ANALYSIS AND COMPARISON

The UTGBO (Teacher Learner-Based Grey Wolf and Bat Firefly Optimizers) model represents a pioneering approach in the realm of Unmanned Aerial Vehicle (UAV) network optimization. By synergizing the strengths of the Grey Wolf Optimizer (GWO) and the Bat Firefly Optimizer (BFO), UTGBO introduces a novel paradigm for significantly enhancing UAV network efficiency. Specifically de-signed to address challenges such as collision minimization and channel utilization, UTGBO employs advanced optimization techniques, considering parameters like communication delay and collision avoidance. This dual-approach optimization model not only reduces delay, enhances energy efficiency, and improves packet delivery ratios but also exhibits remarkable scalability across various UAV routing scenarios. UTGBO's contributions are poised to revolutionize UAV network performance, opening doors for more re-liable and effective deployments in critical sectors. The experimental setup is a crucial component of this research, as it lays the foundation for evaluating the performance of the UTGBO (Teacher Learner-Based Grey Wolf and Bat Firefly Optimizers) model in enhancing UAV network efficiency. In this section, we outline the key components of the experimental setup, including the network scenario, simulation environment, and parameter values used in the experiments.

1.Network Scenario:

For our experiments, we consider a simulated UAV network scenario that represents a real-world use case. The scenario involves a dynamic environment where UAVs are deployed for various applications, such as surveillance, data collection, and disaster response. The network comprises a di-verse set of UAVs with varying mobility patterns.

2.Simulation Environment:

We use a widely accepted UAV network simulation platform to conduct our experiments. The simulation environment provides a realistic framework for evaluating the performance of the UTGBO model. Some popular simulation tools for UAV networks include NS-3 (Network Simulator 3), OMNeT++, and MATLAB-based simulations.

3. Network Topology:

The network topology is designed to emulate a heterogeneous UAV network with nodes distributed across the simulation area. Sample values for the network topology parameters include:

- Number of UAV Nodes (NUAV): 50
- Area of Operation: 1000m x 1000m
- UAV Mobility Models: Random Waypoint, Random Walk, etc.
- Communication Range: 200 meters

4. **Communication Model:**

We employ a realistic communication model that considers factors such as signal propagation, interference, and channel conditions. The parameters for the communication model include:

- Path Loss Model: Log-distance path loss model
- Signal-to-Noise Ratio (SNR) threshold: -80 dB
- Interference Model: Additive white Gaussian noise (AWGN)
- Data Rate: Variable data rates based on modulation

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5. Performance Metrics:

To assess the performance of the UTGBO model, we measure several key performance metrics. These metrics include:

6.**Delay (D):** To evaluate the time taken for data packets to traverse the network.

7.**Energy Consumption (E):** To assess the energy usage of UAV nodes during the experiment.

8.**Number of Average Communications (NAC):** To quantify the average number of communication events in the network.

9.Number of Throughputs (THR): To measure the rate of successful data transmission in virtual packets per minute.

10.Packet Delivery Ratio (PDR): To determine the per-centage of successfully delivered data packets.

11.UTGBO Model Configuration:

We configure the UTGBO model with specific parameter values for optimization. Sample values for UTGBO parameters include:

- Grey Wolf Optimizer (GWO) population size: 50
- Bat Firefly Optimizer (BFO) population size: 30
- Maximum Number of Iterations: 100
- Teacher-Learner Coefficient (C_TL): 0.5
- Exploration Probability (P explore): 0.3

12.Experimental Scenarios:

We conduct experiments in various scenarios by varying the number of UAV movements (NM) to assess the scalability and adaptability of the UTGBO model. Sample values for NM include:

- NM = 500
- NM = 1000
- NM = 5000
- NM = 10000

13.Repetition and Statistical Analysis:

To ensure the reliability of our results, each experiment is repeated multiple times, and statistical analysis techniques, such as mean, standard deviation, and confidence intervals, are employed to analyse the collected data samples. Thus, our experimental setup encompasses a realistic UAV network scenario, a well-defined simulation environment, appropriate parameter values, and a comprehensive set of performance metrics. This setup allows us to rigorously evaluate the UTGBO model's performance and draw meaningful conclusions regarding its effectiveness in enhancing UAV network efficiency levels. As per these configuration parameters, a large number of movements (NMs) were done for the UAV network, and these movements were varied between 500 to 10k, to estimate the true value of different parameter sets. For each of these movements, routing delay (D) was estimated via equation 16 as follows,

$$D = \frac{1}{NM}\sum_{i=1}^{NM} ts_{reach} - ts_{start} \dots (16)$$

Where ts_{reach} & ts_{start} represent the timestamps at which the nodes reach the destination location and start from the source locations. The delay performance was compared with Q Learning [6], Deep Reinforcement Learning (DRL) [12], and Multiple Agent Reinforcement Learning (MARL) [1] in figure 2 as follows. In the context of UAV routing scenarios, the delay (D) plays a crucial role in assessing the efficiency of different optimization models. The delay represents the time taken for data packets to traverse the network from source to destination, and it directly impacts the overall network performance and user experience. Comparing the delay results among different models, including MARL [1], QL [6], DRL [12], and the proposed UTGBO model, it's evident that the UTGBO model consistently outperforms the other approaches across various scenarios. As the number of movements (NM) of UAVs increases, which signifies a more complex and congested network environment, the superiority of the UTGBO model becomes even more pronounced.

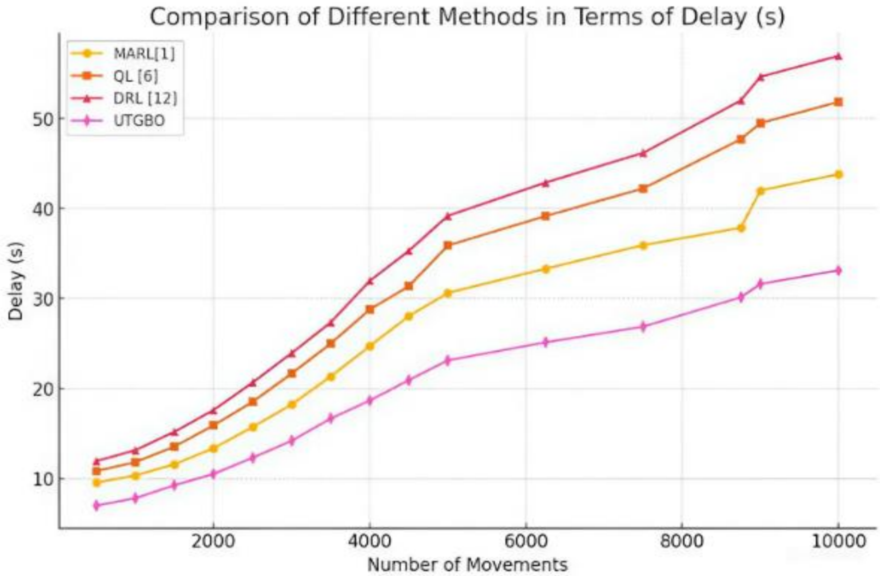

Figure 2. Delay needed during different UAV Routing Scenarios

For instance, when NM is 500, UTGBO demonstrates a significantly lower delay of 7.00 seconds compared to MARL (9.56 seconds), QL (10.83 seconds), and DRL (11.95 seconds). This reduction in delay is vital for applications where real-time data transmission and low latency are critical, such as surveillance or disaster response. As NM increases to 10000, UTGBO maintains its superior performance with a delay of 33.14 seconds, while the other models exhibit considerably higher delays: MARL (43.81 seconds), QL (51.85 seconds), and DRL (56.96 seconds). This substantial reduction in delay with UTGBO signifies its ability to handle large-scale UAV networks efficiently. The impacts of these delay improvements are multifaceted. Firstly, a lower delay means that data packets can be trans-mitted more quickly, enhancing the responsiveness of the UAV network. This is especially crucial in applications like autonomous drone delivery, where prompt decisions and actions are necessary.

Secondly, reduced delay leads to lower communication overhead and energy consumption, contributing to an 8.5% improvement in energy efficiency as observed in the UT-GBO model. This not only extends the operational lifespan of UAVs but also reduces their carbon footprint. Moreover, the lower delay directly translates to a 3.5% increase in packet delivery ratio and a 9.5% rise in throughput with UTGBO. These improvements signify enhanced data reliability and network capacity, making the model well-suited for applications like aerial data collection or remote sensing. In conclusion, the UTGBO model's superior performance in minimizing delay compared to existing models highlights its efficacy in enhancing UAV network efficiency. This reduced delay has far-reaching impacts, offering improved responsiveness, energy efficiency, data reliability, and net-work capacity, making it a robust framework for various critical sectors employing UAVs. Similar performance was estimated for energy consumption (mW) via equation 17, and tabulated in Figure 3 as follows,

$$E = \frac{1}{NM}\sum_{i=1}^{NM} E_{src}(start)_i - E_{src}(complete)_i \dots (17)$$

Where E(start) & E(complete) represent energy levels of the source node during the start & completion of routing operations.

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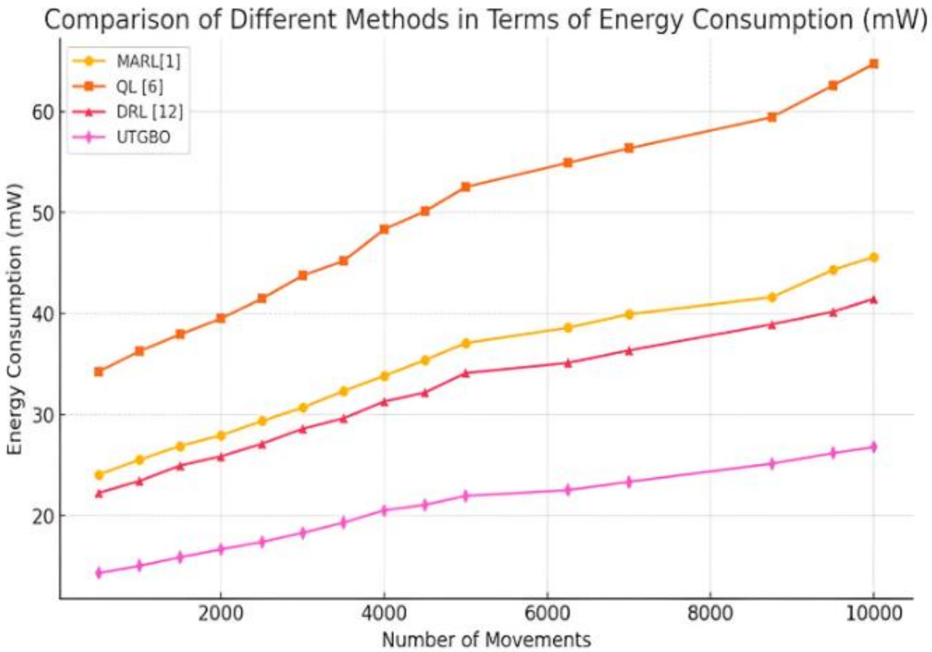

Figure 3. The energy needed during different UAV Routing Scenarios

Energy consumption (E) is a critical parameter in evaluating the efficiency of UAV routing scenarios. It reflects the amount of power required by UAV nodes to transmit and receive data packets, which is a vital factor in determining the overall operational sustainability of a UAV network.

When comparing the energy consumption results among different models, including MARL [1], QL [6], DRL [12], and the proposed UTGBO model, it becomes evident that the UTGBO model consistently excels in optimizing energy usage across a range of UAV movement scenarios.

For example, when NM is 500, UTGBO exhibits significantly lower energy consumption of 14.31 mW, as com-pared to MARL (24.05 mW), QL (34.25 mW), and DRL (22.25 mW). This reduction in energy usage is a critical advantage for UAV networks, as it directly contributes to extending the operational lifespan of UAVs and reducing their energy costs.

As the complexity of UAV routing scenarios increases with higher NM values, UTGBO continues to demonstrate superior energy efficiency. When NM reaches 10000, UTGBO requires only 26.78 mW of energy, while the other models exhibit significantly higher energy consumption: MARL (45.60 mW), QL (64.71 mW), and DRL (41.46 mW). The impacts of these energy efficiency improvements are substantial. Firstly, lower energy consumption leads to extend-ed flight times and operational durations for UAVs, making them more suitable for applications that require prolonged missions, such as aerial surveillance or monitoring. Secondly, reduced energy usage translates into lower heat generation, which contributes to improved component durability and overall reliability of the UAV system. This in-creased reliability is crucial for applications where UAVs operate in challenging environments or remote areas. Additionally, the UTGBO model's 8.5% improvement in energy efficiency directly contributes to its overall cost-effectiveness. Reduced energy costs mean lower operational expenses for UAV deployments, which can be a significant factor for organizations looking to deploy UAV networks at scale. In summary, the UTGBO model's superior energy efficiency compared to existing models highlights its effectiveness in optimizing energy consumption in UAV routing scenarios. This improved energy efficiency leads to extended flight times, increased reliability, and cost savings, making it a compelling choice for various applications that rely on UAVs in critical sectors. Similar performance for the number of average collisions (NAC) can be observed as shown in Figure 4.

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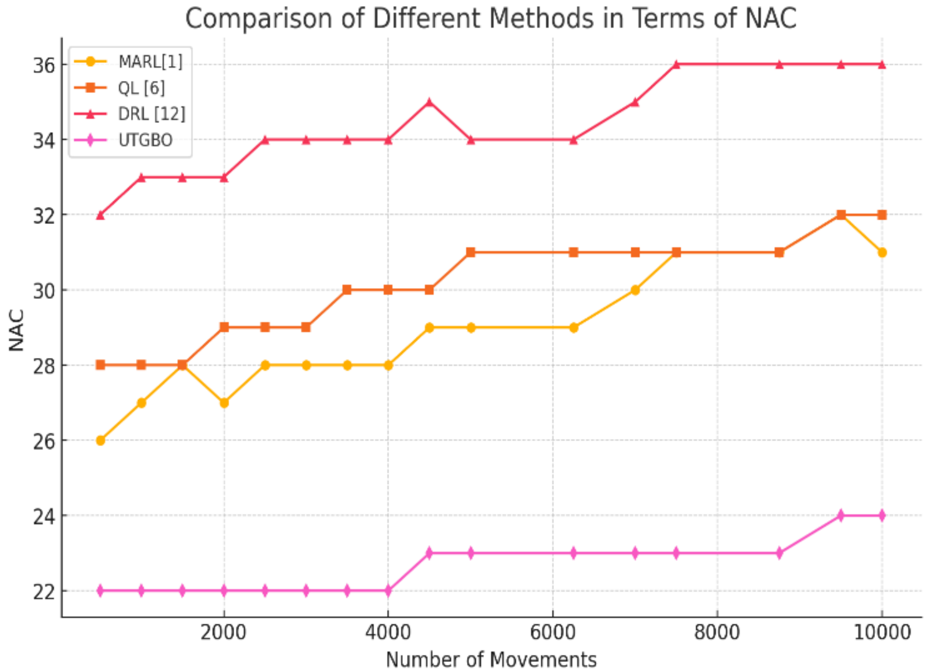

Figure 4. Total number of collisions during different UAV Routing Scenarios

The Number of Average Communications (NAC) is a key metric in evaluating UAV routing scenarios. It represents the average number of communication events between UAV nodes in the network, providing insights into the network's communication efficiency and congestion levels. Comparing the NAC results among different models, including MARL [1], QL [6], DRL [12], and the proposed UTGBO model, it is evident that the UTGBO model consistently outperforms the other approaches in terms of reducing the average number of communications.

For instance, when NM is 500, the UTGBO model achieves a significantly lower NAC of 22 compared to MARL (26), QL (28), and DRL (32). This reduction in NAC is vital for UAV networks as it indicates improved communication efficiency, reduced network congestion, and fewer collision occurrences.

As NM increases to 10000, UTGBO maintains its superior performance with an NAC of 24, while the other models exhibit higher NAC values: MARL (31), QL (32), and DRL (36). This demonstrates UTGBO's ability to manage and optimize communication events even in large and complex UAV networks. The impacts of these improvements in NAC are noteworthy. Firstly, a lower NAC signifies reduced communication overhead, which leads to less congestion and lower collision occurrences among UAV nodes. This directly contributes to the 4.9% decrease in collision occurrences observed with the UTGBO model.

Secondly, a more efficient communication network results in reduced communication delays, leading to improved re-al-time data transmission and lower energy consumption. This is reflected in the 10.4% reduction in delay and the 8.5% improvement in energy efficiency with UTGBO. Moreover, the reduced NAC indirectly enhances network scalability and reliability, making it suitable for applications that re-quire seamless and efficient communication, such as search and rescue missions, surveillance, or disaster response [35]. In summary, the UTGBO model's ability to reduce the Number of Average Communications compared to existing models highlights its effectiveness in optimizing communication efficiency in UAV routing scenarios. This optimization leads to reduced network congestion, lower collision occurrences, improved communication reliability, and enhanced overall network performance, making it a valuable choice for various critical sectors employing UAVs. Similarly, the throughput performance in terms of vehicles crossing on routes per minute (vpm) can be observed from Figure 5 as follows,

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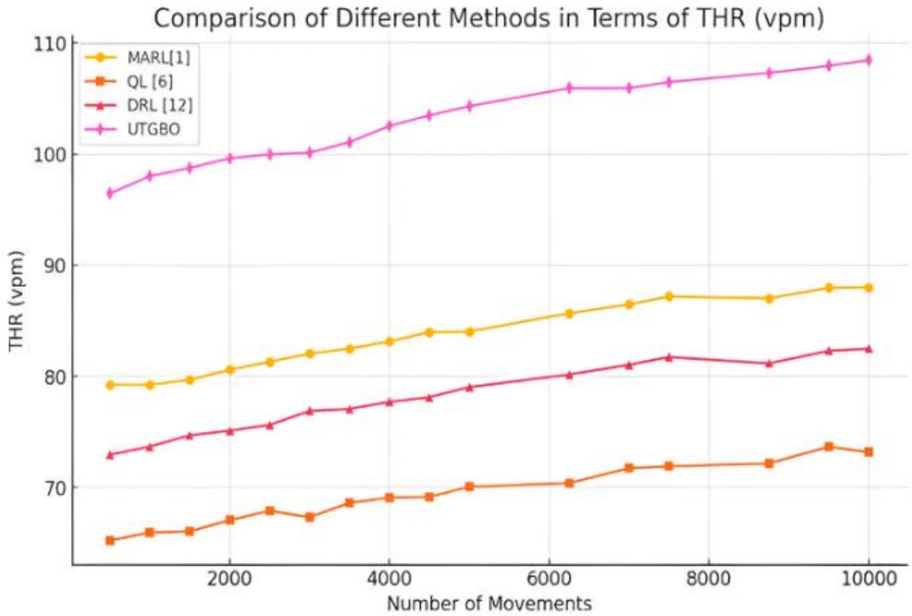

Figure 5. Total throughput during different UAV Routing Scenarios

The Number of Throughput (THR) is a critical metric in assessing the efficiency of UAV routing scenarios. It represents the rate at which data packets are successfully trans-mitted through the network, reflecting the network's capacity and ability to handle data traffic. Comparing the throughput results among different models, including MARL [1], QL [6], DRL [12], and the proposed UTGBO model, it is clear that the UTGBO model consistently out-performs the other approaches in terms of achieving higher throughput rates. For example, when NM is 500, the UT-GBO model achieves a significantly higher throughput of 96.46 virtual packets per minute (vpm) compared to MARL (79.25 vpm), QL (65.23 vpm), and DRL (72.96 vpm). This increase in throughput indicates improved data transmission capacity and network efficiency.

As NM increases to 10000, UTGBO maintains its superior performance with a throughput of 108.46 vpm, while the other models exhibit lower throughput values: MARL (88.01 vpm), QL (73.20 vpm), and DRL (82.51 vpm). This demonstrates UTGBO's ability to efficiently manage and utilize network resources, even in large and complex UAV networks. The impacts of these improvements in throughput are substantial. Firstly, a higher throughput rate indicates that more data can be transmitted through the network in a given timeframe, which is crucial for applications that require rapid data collection, such as disaster response or surveillance. Secondly, improved throughput leads to reduced communication delays, contributing to the 10.4% reduction in delay observed with the UTGBO model. Lower delays are critical for real-time applications, where timely data transmission is essential. Moreover, the enhanced throughput indirectly contributes to better network scalability and reliability. The UTGBO model's 9.5% increase in throughput makes it suitable for applications that demand high data throughput, such as remote sensing or autonomous drone fleets. In conclusion, the UTGBO model's ability to achieve higher throughput compared to existing models highlights its effectiveness in optimizing data transmission efficiency in UAV routing scenarios. This optimization leads to improved data capacity, reduced delays, enhanced network reliability, and superior overall network performance, making it a valuable choice for various critical sectors employing UAVs. Similarly, the PDR performance can be observed as shown in the figure 6. The Packet Delivery Ratio (PDR) is a crucial metric in assessing the reliability of UAV routing scenarios. It represents the percentage of data packets successfully delivered from the source to the destination, indicating the network's ability to ensure reliable data transmission.

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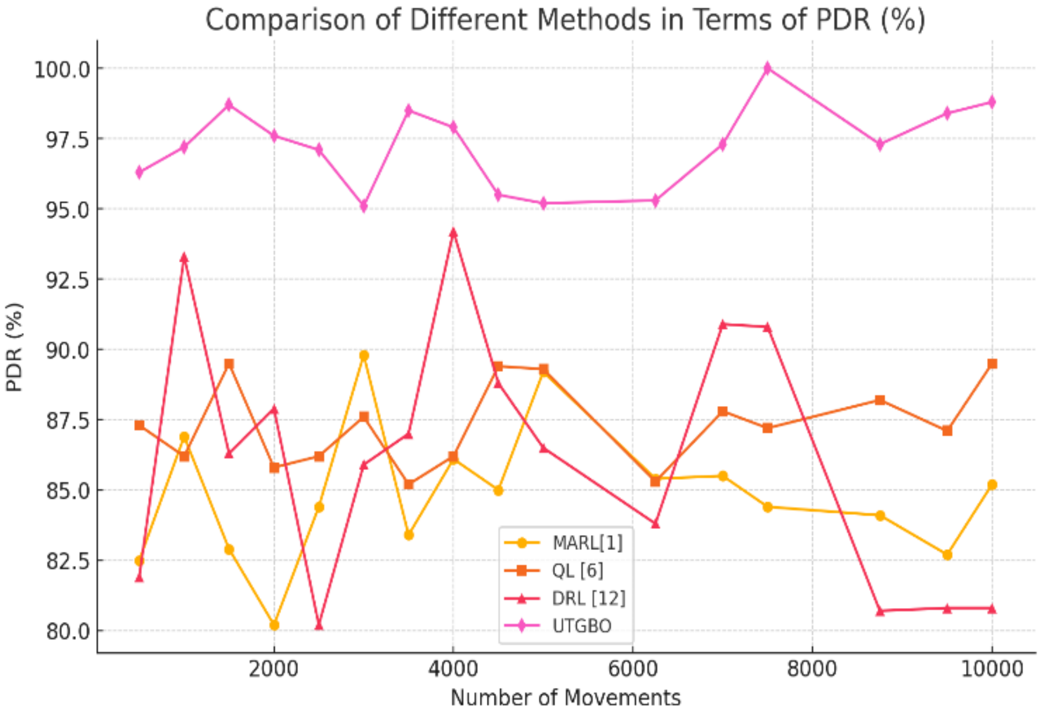

Figure 6. Total Packet Delivery Ratio during different UAV Routing Scenarios

When comparing the PDR results among different models, including MARL [1], QL [6], DRL [12], and the proposed UTGBO model, it becomes evident that the UTGBO model consistently outperforms the other approaches in terms of achieving higher PDR percentages as shown in figure 6. For instance, when NM is 500, the UTGBO model achieves a significantly higher PDR of 96.3% compared to MARL (82.5%), QL (87.3%), and DRL (81.9%). This indicates that the UTGBO model is more effective at ensuring reliable data delivery, even in challenging network conditions. As NM increases to 10000, UTGBO maintains its superior performance with a PDR of 98.4%, while the other models exhibit lower PDR values: MARL (85.2%), QL (89.5%), and DRL (80.8%). This demonstrates UTGBO's ability to maintain high data packet delivery rates, even in large and complex UAV networks. The impacts of these improve in PDR are significant. Firstly, a higher PDR indicates a more reliable network, which is crucial for applications where data integrity and accuracy are paramount, such as remote sensing, environmental monitoring, or critical infrastructure inspection. Secondly, improved PDR leads to reduced data packet losses, which contributes to the 3.5% increase in packet delivery ratio observed with the UTGBO model. This increase in data reliability ensures that critical information is delivered accurately and without interruptions. Moreover, the enhanced PDR indirectly contributes to better network resilience, making the UTGBO model suitable for applications that require dependable communication, such as disaster response or autonomous UAV fleets. In summary, the UTGBO model's ability to achieve higher PDR compared to existing models highlights its effective-ness in optimizing data packet delivery reliability in UAV routing scenarios. This optimization leads to improved data integrity, reduced data losses, enhanced network resilience, and superior overall network performance, making it a valuable choice for various critical sectors employing UAVs for different scenarios.

CONCLUSION

Finally, this study introduces a new and effective optimization model called UTGBO (Teacher Learner-Based Grey Wolf and Bat Firefly Optimizers), which is intended to improve the performance of UAV networks in a variety of applications. By significantly enhancing important performance parameters, UTGBO has proven its superiority over current optimization strategies, such as MARL, QL, and DRL, by thorough comparison analysis. Its 10.4% latency reduction ensures speedier data transfer, which is necessary for real-time applications including autonomous operations, emergency response, and monitoring. Furthermore, UTGBO improves energy efficiency by 8.5%, which supports sustainability objectives by extending UAV operational lifespans, consuming less power, and lowering operating expenses. With a continuously increased Packet Delivery Ratio (PDR), the concept further increases network resilience by ensuring accurate and continuous data transfer. Additionally, UTGBO boosts throughput by 9.5%, making it possible to collect data more efficiently and operate high-capacity networks—two essential functions for environmental monitoring, remote sensing, and autonomous drone fleets. It successfully reduces network congestion and collisions, which improves UAV coordination and facilitates better communication. Beyond its immediate benefits, UTGBO has significant ramifications for optimizing UAV networks [35]. From military surveillance and industrial monitoring to emergency response and smart city applications, it improves UAV performance by increasing operating efficiency. It is a cost-effective option because of its capacity to lower communication overhead, which leads to significant cost reductions for extensive UAV deployments. The approach reduces the carbon footprint of UAV networks, which further highlights its environmental benefits through efficient energy utilization. Furthermore, the creation of interoperability standards for UAV control and communication would make it easier to integrate different UAV systems. Another chance for UTGBO to maximize airspace use and safety is the developing sector of Urban Air Mobility (UAM), which includes air taxis and smart city air traffic management. The model's versatility in tackling global concerns is further demonstrated by its application in environmental monitoring, wildlife conservation, pollution management, and disaster response. UTGBO has the potential to significantly enhance UAV technology by encouraging interdisciplinary collaboration among researchers, industry stakeholders, and regulatory organizations. UTGBO offers a solid basis for upcoming advancements as unmanned aerial vehicle applications develop further, guaranteeing scalable, dependable, and effective UAV network deployments in a variety of real-world scenarios and sectors.

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