International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Integrating Long Short-Term Memory and Reinforcement Learning in Federated Learning Frameworks for Energy-Efficient Signal Processing in UAV-Assisted Wireless Communication Networks

Sumthane Mahesh Yadavrao[*1], Dr. Kirti Saraswat[2]

Submitted: 06/02/2024 **Revised**: 14/03/2024 **Accepted**: 20/03/2024

Abstract : This paper presents a comprehensive study of signal processing algorithms designed for enhancing the energy efficiency of UAV-aided wireless communication networks. We explore a sequence of advanced machine learning techniques, each tailored to address specific challenges within the network. We begin by detailing the application of Long Short-Term Memory (LSTM) networks, which are adept at uncovering patterns in data with unknown objectives or constraints. Echo-State Networks (ESNs) are then introduced for their proficiency in sequence and pattern detection, essential for classification and regression prediction problems in signal processing. We further examine the role of Reinforcement Learning (RL) in actively engaging with prediction problems and NP-hard problems, leveraging a reward-based system to facilitate active learning. In addressing the critical concerns of data privacy and excessiveness, Federated Learning (FL) is proposed as a decentralized solution that promotes local training on UAVs, significantly reducing the need for data centralization. Through the methods outlined, we achieve a novel optimization framework that integrates the aforementioned techniques, commencing with the identification and mitigation of unwanted vehicles in the network, which is processed into a Data Traffic Matrix. This feeds into an LTE DIC algorithm based on correlation and culminates in an optimization process that considers specific network parameters 'P' and 'B'. The results, derived from the comparative analysis using the established techniques, indicate a significant improvement in network efficiency. The proposed framework demonstrates a marked enhancement in energy efficiency, with an observed improvement percentage over existing methods. This substantiates the efficacy of the integrated approach, suggesting that the application of machine learning algorithms can lead to superior performance in UAV-assisted networks, providing a significant step forward in the development of autonomous and efficient wireless communication systems.

Keywords : UAV, Long Short-Term Memory, Reinforcement Learning, signal processing, wireless communication networks, Federated Learning , energy efficiency.

1. Introduction

Unmanned Aerial Vehicles (UAVs) have become pivotal in modern wireless communication networks, offering agile deployment, dynamic network topology, and a unique vantage point for data collection and dissemination. The integration of UAVs into communication networks, however, introduces complex challenges, particularly in signal processing and energy efficiency. As UAVs typically operate on limited battery resources, optimizing their energy usage while ensuring robust signal processing capabilities is paramount. This paper focuses on harnessing the strengths of Long Short-Term Memory (LSTM) networks, Reinforcement Learning (RL), and Federated Learning (FL) to improve the energy efficiency of signal processing in UAV-assisted wireless communication networks.

The LSTM networks, known for their effectiveness in handling sequential data, are particularly suited for the time-dependent nature of signal processing tasks in UAV communications. They can model and predict complex temporal behaviors, which is crucial for tasks such as dynamic resource allocation, predictive maintenance, and adaptive signal filtering. On the other hand, RL's capability to make sequential decisions through trial and error makes it an ideal approach for adapting to the UAV's operational challenges in real-time, optimizing decisions for path planning, and resource management to enhance energy efficiency.

Meanwhile, FL emerges as a novel learning paradigm that addresses the growing concerns over data privacy and the need for decentralized data processing. In UAV networks, FL can facilitate collaborative learning among distributed UAVs without sharing the raw data, thereby preserving privacy and reducing the communication overhead associated with centralized data processing. This decentralized approach also aligns with the need for

[1] *Research Scholar,*
Department of Electronics and Communication Engineering,
Dr. APJ Abdul Kalam University, Indore, India
[2] *Research Supervisor,*
Department of Electronics and Communication Engineering,
Dr. APJ Abdul Kalam University, Indore, India
Email : sumthane.mahesh16@gmail.com , ksaraswat1503@gmail.com
* *Corresponding Author Email:* sumthane.mahesh16@gmail.com

scalable and adaptive solutions in large-scale UAV deployments.

The convergence of these advanced machine learning techniques—LSTM for its sequential data processing, RL for its decision-making prowess, and FL for its privacy-preserving and decentralized nature—presents a unified framework that could revolutionize the way UAV networks process signals and manage energy resources. The proposed integrative approach aims to leverage the LSTM's ability to make accurate predictions, the RL's adaptability to environmental dynamics, and the FL's capacity for collaborative learning to substantially improve the overall efficiency of UAV-assisted wireless communication networks.

The key points to consider:

1. **Machine Learning Techniques**: Integration of Long Short-Term Memory (LSTM) networks and Reinforcement Learning (RL) has been identified as essential for handling the sequential data and decision-making challenges in UAV-assisted wireless communication networks.

2. **Energy Efficiency**: The primary goal of leveraging these advanced algorithms is to enhance energy efficiency within UAV networks, which is crucial given the limited power resources of UAVs.

3. **Signal Processing**: LSTM is particularly noted for its pattern detection capabilities, which is a critical feature for complex signal processing tasks that are fundamental to UAV operations.

4. **Dynamic Optimization**: RL is employed for its ability to learn and make decisions actively, which is beneficial for dealing with dynamic optimization problems and NP-hard problems within the network.

5. **Federated Learning**: FL addresses challenges related to excessive data and privacy concerns through local training on distributed UAVs, reducing the need for central data collection.

6. **Problem Types and Solutions**: The integration of these techniques provides solutions to a range of problem types, from unknown objectives and constraints to classification, regression prediction, and privacy issues.

7. **Performance Improvement**: The proposed integration of LSTM, RL, and FL is shown to improve performance significantly, as indicated by the percentage improvement over existing methods.

8. **Framework for Optimization**: A novel optimization framework is suggested that begins with the identification of unwanted vehicles and progresses through data traffic matrix analysis, LTE DIC based on correlation, and optimization based on specific parameters ('P' and 'B').

9. **UAV Network Integrity**: The framework seeks to maintain network integrity and performance in the presence of unwanted vehicles by optimizing vehicle performance within the network.

The paper is structured into five sections: an introduction that sets the context, a literature review that surveys existing research, a proposed section detailing the new methodology, a results and discussion section that evaluates the findings, and a conclusion that summarizes the key takeaways.

2. Literature Review

According to **Maheswar et al. (2024),** there has been a dramatic increase in the use of wireless devices across a wide variety of industries. The post-COVID-19 period had a particularly significant influence, sparking a worldwide revolution in the use of wireless technologies. During this age, there have been tremendous developments in both the number of devices connected to networks and the variety of uses for these devices, which include sensors, IoT devices, mobile phones, and many more wireless electronic devices. In spite of the tremendous difficulties brought on by the epidemic, these technical developments have been critical in maintaining smooth worldwide communication. The massive use of wireless devices in the epidemic brought to light a serious issue—the enormous amount of energy that these gadgets use due to their widespread use in homes, schools, and businesses. Improving energy efficiency is a critical need since most wireless devices use batteries. If we want our gadgets and the networks they are a part of to last as long as possible, we need efficient methods of managing and controlling their energy use. [1]

According to **Jeganathan et al. (2023),** the Internet of Things (IoT) is a key component of the fourth industrial revolution. Unlike speed in cellular communications, an essential metric in the Internet of things (IoT) is the freshness of the data provided by a sensor node (SN). In this study, we employ a novel performance metric called age of information (AoI) to measure how recent the data is. Power is derived from the FD-UAV's radio frequency communications by the SN, which is housed in the transportation infrastructure. The data sink receives real-time sensor observations using FD-UAV. Once the battery is recharged, the SN uses the energy it has captured to broadcast an update. The average AoI may be expressed in a closed-form manner by varying the amount of time that is set aside for energy collecting. We found the best way to divide up our energy collecting time so that our data is always up-to-date. To forecast the mean AoI, a deep learning method called long-short term memory is used. The simulation results show that the performance constraints are helpful when considering how recently updated the data. [2]

According to **Rose et al. (2024),** NOMA wireless networks provide a reliable method for handling several customers requesting the same resource block at the same time. Using fifth-generation wireless networks' very efficient spectrum utilisation, unmanned aerial vehicles (UAVs) may use NOMA for line-of-sight (LOS) communication. Access equity, coverage, system capacity optimisation, and overall energy efficiency are just a few of the many facets of NOMA-UAV communication systems that have been the subject of much prior study. Nevertheless, optimising the EE of NOMA-UAV wireless networks while imposing QoS limits on users has received very little attention from academics. In order to optimise the energy economy of NOMA-UAV and user scheduling, this study suggests a crossover-based coati optimisation technique that is based on fuzzy logic. This model's primary goal is to provide an answer to the scheduling issue that involves both energy efficiency and user quality of service. In order to maximise NOMA-UAV's energy efficiency (EE), the fuzzy decision-making approach chooses the most suitable power and time resources. And the subchannel allocation issue becomes a two-sided matching operation with the help of the crossover-based coati optimisation algorithm. Total residual energy, number of surviving nodes, and time consumption are used to assess the efficiency of the proposed method. The experimental results show that the suggested model can maximise the NOMA-UAV network's energy efficiency by determining the best combination of time and power resources to meet the quality of service requirements of the customers. [3]

Drones, or unmanned aerial vehicles (UAVs), have seen a meteoric rise in popularity in recent years, according to **Ghamari et al. (2022).** The increasing demand for the use of such platforms, especially in civil applications, and the fast progress in their design and manufacture have led to this. UAVs that are both affordable and reliable have become more common. Unmanned Aerial Vehicles (UAVs) offer a lot of promise for use in wireless systems due to their inherent characteristics, such as their great mobility, quick deployment, and adjustable height. One the one hand, unmanned aerial vehicles (UAVs) may serve a range of tasks including remote sensing, search and rescue, precision agricultural monitoring, and commodities delivery by acting as mobile terminals in the air inside wireless and cellular networks. Conversely, unmanned aerial vehicles (UAVs) have the potential to serve as base stations in the sky, expanding the reach, capacity, and dependability of wireless networks without the need to install costly new infrastructure. In this piece, we will take a look at some of the current commercial and civic uses of unmanned aerial vehicles (UAVs). This research delves into the difficulties and necessary communication protocols for UAV-based communication systems. Several factors, including those affecting UAVs' ability to communicate, are used to categorise UAVs in the article. Following that, it delves into the topic of aerial networking and examines UAV routing protocols in particular, a problem area in UAV communication. Afterwards, the paper delves into the several civic applications of UAV networks, exploring the numerous obstacles and communication requirements associated with these uses. After that, we take a look at several simulation systems from a networking and communication perspective. In the end, it pinpoints places where more study is needed. [4]

In order to accomplish the Sustainable Development Goals (SDGs), contemporary civilization relies on precision agriculture, often called smart farming (**Massaoudi et al., 2023**). The goal of precision agriculture is to increase yields while decreasing use of finite resources. In recent years, smart farming has expanded as a result of the incorporation of contemporary technology, such as the Internet of Things (IoT) and artificial intelligence (AI). In this study, we investigate the feasibility of using UAVs as part of an irrigation system for olive trees. In particular, UAVs guarantee remote sensing (RS), which has the benefit of gathering critical data on a massive geographical and temporal scale (unattainable with conventional technology). Nevertheless, there are many linked components that need sophisticated computational capabilities, large battery capacities, energy economy, and spectrum efficiency, which presents a significant barrier for UAV-based irrigation systems. An issue with UAV-based irrigation systems is the trade-off between energy efficiency and spectral efficiency, which is addressed in this research. We recommend using M-MIMO technology, which stands for massive multiple input, multiple output, to guarantee wireless connection. Not only does this technology hold promise for improved energy and spectrum efficiency, but it also plays a key part in the next generation of wireless mobile networks, the sixth generation (6G). We develop a three-layer network model and calculate analytically the system's potential spectral and energy efficiency. We next utilise numerical methods to find the ideal quantity of Internet of Things (IoT) devices and ground base station antennas to achieve optimum energy efficiency with high spectral efficiency guaranteed. Using the M-MMSE combiner, the numerical results show that the proposed UAV-based irrigation system achieves the optimum spectral and energy efficiency trade-off, and it also outperforms traditional systems. [5]

Unmanned aerial vehicles (UAVs) and the Internet of Things (IoT) have seen tremendous technical progress, which has changed our lifestyle choices (**Gupta et al., 2022**). Academics are interested in studying UAVs since they connect everything in the current world. Unmanned Aerial Vehicles (UAVs) have already shown to be a global blessing by providing air support during life-threatening medical crises. Unmanned Aerial Vehicles (UAVs) are a kind of cutting-edge technology that will help humanity advance towards a smarter future by meeting a wide range of demands. Many sensors and flying nodes in UAV-assisted conventional networks require a lot of power, and gadgets allowed by Fifth Generation (5G) or beyond 5G release a lot of radiation, which might harm our society and the environment. Consequently, a better lifestyle can only be achieved by balancing environmental protection with the use of contemporary technology. This can only be sustained with ongoing efforts to lessen the load on nodes, cut down on data resource usage, and promote efficient energy-use practices. An intelligent world with better Quality of Services (QoS) may be built via the use of green UAV-based fog computing, which offers a solution to environmental challenges while also providing energy-efficient data processing and aerial-to-ground network connection. An extensive overview of environmentally friendly technologies and their potential uses for UAV-Fog is presented in this article. In addition, we focus on research topics, present difficulties, lessons gained, and the UAV-Fog network's future plans. [6]

A variety of scenarios may benefit from unmanned aerial vehicle (UAV) networks, including public safety, advertising, broadcasting, disaster management, and more (**Alkanhel et al., 2023**). The ever-changing nature of mobile users makes it difficult to provide them with reliable communication services. To enhance the coverage and energy efficiency of UAV-assisted transmission networks, it is essential to address the transmission issue of resource allocation, which encompasses subchannels, transmit power, and user service. In this study, we introduce ESMOL-RAA, an improved slime mould optimisation method for UAV-enabled wireless networks that makes use of deep learning. Decisions that are both computationally and energy-effective may be effectively accomplished with the help of the ESMOML-RAA approach. Furthermore, the ESMOML-RAA method formulates a reward function with the goal of minimising weighted resource consumption and takes into account a UAV as a learning agent with the creation of a resource assignment choice as an action. The offered ESMOML-RAA method uses an HP-LSTM model, which is a hyperparameter optimizer for an ESMO algorithm, to distribute resources. To fine-tune the HP-LSTM model's hyperparameters, the ESMO method is useful. A battery of simulations is used to validate the ESMOML-RAA technique's performance. The ESMOML-RAA method outperformed the competing ML models in this comparative analysis. [7]

In order to improve network spectrum, energy efficiency, and data transfer rate, future 5G/6G communication will rely significantly on efficient and low-latency wireless cellular device-to-device communication (**Luo and Fu, 2023**). Improving energy-efficient communication while considering latency is made possible by using modern technologies like swarm optimisation and deep learning. Intelligent and efficient data control and transmission technologies are necessary for networks of the fifth and beyond generations. In order to set up low-power, high-transfer-rate data transmission between equipment, unmanned aerial vehicles (UAVs) are used. Emphasising the need of integration with potential solutions to improve network performance, this research also centres on integrating UAV-based D2D communication with other sophisticated technologies. To keep up with the ever-increasing needs of wireless networks, researchers are working on 5G and 6G communication technologies to provide better device and application compatibility, higher data rates, reduced latency, and more reliable connections. On the other hand, in order to adapt to the impending digital landscape, the existing network advantages will need to be strengthened. Therefore, we provide a fresh strategy for UAV-based device-to-device communication that makes use of optimised deep learning models in three ways to tackle these challenges: 1. Hybrid Particle Swarm Optimisation with an Effective K-means Clustering Method (IHPSO-K) Version 2. In order to overcome the limitations that UAVs encounter while trying to fulfil the most recent technical standards, researchers have developed a Hybrid Fuzzy C Means (HFCM) technique and a three-greedy algorithm. We use two approaches—the device-centric approach and the network-centric approach—to carry out the efficient performance of the suggested algorithm, taking into account the qualities mentioned above. In UAV-based D2D communication, combining these methods may lead to more precise and efficient data clustering. Crucial aspects of such communication situations include throughput, latency, and energy usage; this may lead to better performance in all three areas. [8]

El-Gayar and Ajour (2023) discuss how important it is for communication systems to improve energy economy, content distribution, latency, and transmission speeds. To improve these KPIs, many access methods show a lot of potential. Within a single cell, with users dispersed at random and depending on relays for reliability, this publication assesses the efficacy of Orthogonal Multiple Access (OMA) and Non-Orthogonal Multiple Access (NOMA) systems. In this study, we provide a paradigm for single-cell NOMA and OMA communication systems that improves energy efficiency, content distribution, latency, and transmission speeds. In addition, the authors of this work suggest a caching technique that makes use of UAVs as mobile data centres above ground. By repositioning themselves and distributing cached material, these UAVs reduce the total latency of content requests from terrestrial users. We ran simulations with different cache capacity and user numbers associated with UAVs. In addition, we compared OMA and NOMA based on their achieveable rates and energy efficiency. Regardless of the total rate, number of mobility users, cache size, or amount of power allocated, the suggested model has improved significantly. [9]

In the future, the services provided by the planned smart cities will be completely transformed by Unmanned Aerial Vehicles (UAVs) due to their nimbleness, adaptability, and low operating costs (**Alharbi et al., 2022**). Unmanned Aerial Vehicles (UAVs) are seeing extensive deployment across a variety of industries, from surveillance and search and rescue to product delivery and the foundation of future wireless networks' aerial communications. Unmanned Aerial Vehicles (UAVs) have several potential applications, including precise position surveying, data collection from the ground (such as video feeds), and the generation and offloading of computational tasks to servers that are accessible. Here, we use the Mixed Integer Linear Programming (MILP) optimisation paradigm to create a multi-objective optimisation framework that can handle both the UAV trajectory planning issue and the allocation of network resources. Given the diversity of interests that could be present in a Cloud-Fog setting, we take into account all of the potential stakeholders and minimise the sum of a weighted objective function. This gives network operators the freedom to adjust the weights to prioritise certain cost functions, like EENPC, PPC, UAVTFD, and UAVTPC, among others. We thoroughly examine various limitations related to EENPC, PPC, UAVTFD, and UAVTPC, and our optimisation models and outcomes allow for the optimal offloading options to be made under these conditions. To illustrate, the optimal course of action is to offload data to the macro base station when the UAV's propulsion efficiency (UPE) reaches its lowest point of 10%. This will result in a maximum power savings of 34%. While many studies have focused on UAV coverage path planning (CPP) and computation offloading, no one has yet examined this in a real-world Cloud-Fog architecture that takes into account all aspects of the access, metro, and core layers when assessing service offloading in a distributed architecture such as Cloud-Fog. [10]

According to **Alnakhli et al. (2024),** UAVs have become more popular as useful wireless platforms to assist users in a variety of contexts, especially in inaccessible areas such as disaster relief operations. In order to optimise the spectral and energy efficiency of the UAV network, it is necessary to optimise the UAV-user association. This is because this research uses numerous UAVs to cover users in overlapping places. For this purpose, graph theory is used to create a linked bipartite graph including UAVs and users. Next, in order to maximise data rate considering user requests and UAV capabilities, an optimisation method called MwMaxFlow is suggested. Users' transmit powers are optimised and energy efficiency is improved by the use of power control based on the M-matrix theory. Through numerical simulations, the suggested approach is assessed and contrasted with other standard techniques. Results from the simulations show that the suggested method strikes a good balance between energy consumption and spectrum efficiency, making it applicable to a wide range of wireless UAV applications, such as monitoring, emergency response, and disaster management in the aftermath. the eleventh Unmanned aerial vehicles (UAVs) have seen widespread use as a data gathering platform to aid in the efficient collection of data from Internet of Things (IoT) devices [11].

Basset et al. (2024), The need to reduce energy consumption of UAVs and IoT devices has, however, made optimisation of UAV deployment difficult. There have been a number of algorithms suggested as solutions to this problem as of late, but their sluggish convergence time and memory-wasting issues mean that they are far from perfect. In order to optimise the whole deployment of UAVs in a way that minimises total energy usage, this research proposes a novel energy-aware strategy. The foundation of this method is the introduction of a novel encoding mechanism—specifically, an optimised population size mechanism—that effectively represents the position and quantity of stop points. Like in other research, this system holds the whole population to account for the deployment as a whole, with each person accountable for a specific milestone along the way. One innovative approach to optimising the amount of stop points is shown by this method. It uses an auxiliary variable to decide whether a stop point will be deleted, introduced, or replaced in the newly created deployment. Throughout the optimisation process, optimisation algorithms will seek for the best option for each stop point that might lead to a better deployment by optimising this variable. By modifying the gradient-based optimizer (GBoPS) and differential evolution (DE), two popular optimisation methods, this mechanism introduces two new versions—DEoPS and GBoPS—that are more suited to solving the deployment optimisation issue. In this study, we examine the efficiency of DEoPS and GBoPS using two energy consumption models. On eleven separate occasions, researchers have tested DEoPS and GBoPS against a variety of algorithms to see how they fare. The results of the experiments demonstrate that GBoPS worked well with the first formulation and that DEoPS worked well with the second formulation. [12]

Drones are a useful tool for gathering information from wireless sensor networks (WSNs), according to **Ding et al. (2023)**. In this study, we explore the issue of energy-efficient data gathering in a secure WSN that is enabled by UAVs, without knowing the eavesdropper's (Eve) immediate channel state knowledge. In particular, at the predetermined intervals, the UAV gathered data from all of the wireless sensors and sent it to the fusion centre, all the while Eve attempted to eavesdrop on this sensitive data. Our solution to this complex mixed-integer non-convex problem involves minimising the maximum energy consumption of ground sensor nodes (GSNs) while taking into account constraints such as secrecy outage probability (SOP), connection outage probability (COP), minimum secure data, information causality, and UAV trajectory. This optimisation algorithm is iterative and uses the block coordinate descent (BCD) method. The numerical findings show that our suggested method outperforms previous strategies in terms of energy usage and secrecy rate. [13]

In their study, **Sugesh and Vairavel (2023)** found that using ML solutions in UAV-assisted 5G communication may have a positive impact on both 5G and future generations of wireless networks. Concerning the use of machine learning in 5G communication with the help of UAVs, there is a dearth of research at all levels of education. Finding exact answers for UAV-assisted 5G communication is challenging due to what seems to be a lack of such research. Researching and understanding the use of machine learning to UAV-assisted 5G communication is so crucial. Several design and functional characteristics, including beamforming, resource allocation, dynamic deployment, and trajectory prediction, have been enhanced by applying machine learning (ML) methods to UAV-based wireless communication in this article's systematic study of important research activities. In this review, the studies were grouped into four themes: (1) the main machine learning algorithms used in UAV-assisted wireless communication; (2) the main categories of machine learning algorithms and frameworks; and (3) the process of UAV-assisted 5G communication using machine learning. The results show that the main algorithms and frameworks used in UAV-assisted wireless communication are: Q-Learning, MARL, K-means, AMSSA, genetic algorithm, support vector machine (SVM), support vector regression, artificial neural network (ANN), LSM, cross-entropy algorithm, DL algorithm, and reinforcement learning algorithm. [14]

In this study, a new transmission strategy for UAV-assisted air-to-ground (A2G) communication is suggested by **Chen et al. (2023).** The technique is both energy-efficient and dependable. This method is designed to deal with transmission burst mistakes that occur as a result of interference, switching, or collisions in the network. To make A2G communication more reliable, the Application Layer Forward Error Correction (AL-FEC) method is suggested. Retransmissions have must be avoided at all costs in order to ensure energy efficiency. We mathematically analyse the suggested AL-FEC scheme's performance in depth using the Gilbert-Elliott channel model. A number of simulations have been conducted to investigate and verify the energy efficiency and packet delivery ratio. We compare the proposed approach to an application layer Automatic Repeat reQuest (AL-ARQ) protocol that relies on selective retransmission. In comparison to the baseline approach, the suggested AL-FEC method assures the same or an even greater application packet delivery ratio while drastically reducing energy usage. The suggested strategy also shines in situations when the channel quality is low. Practical applications that depend on UAV-assisted A2G communication may benefit from our results, which outline the specifics of achieving dependable and energy-efficient UAV-to-ground transmission in challenging wireless environments. [15]

In their latest work on the RUBER system, which addresses the problems of sensor node and route failure in smart wireless livestock sensor networks, **Bouchekara et al. (2024)** build upon previous work on recoverable UAV-based energy-efficient reconfigurable routing. This study proposes a time-aware UAV-based energy-efficient reconfigurable routing (TUBER) strategy to address the temporal complexity and processing cost concerns associated with the RUBER approach. An approach to redundancy reduction, a minimum-hop neighbourhood recovery method, and synchronised clustering with backup are all components of the TUBER system. Researchers looked studied TUBER's network performance in comparison to RUBER and UAV-based UBER, two systems for energy-efficient reconfigurable routing. Cluster Survival Ratio (CSR), Network Stability (NST), Energy Dissipation Ratio (EDR), Network Coverage (COV), Packet Delivery Ratio (PDR), Fault Tolerance Index (FTI), Load Balancing Ratio (LBR), Routing Overhead (ROH), Average Routing Delay (ARD), Failure Detection Ratio (FDR), and Failure Recovery Ratio (FRR) are the metrics used for this comparison of performance. According to the best-obtained data, TUBER outperformed RUBER and UBER by 36.25%, 24.81%, 34.53%, 15.65%, 38.32%, 61.07%, 31.66%, 63.20%, 68.19%, 66.19%, and 78.63% in the following categories: CSR, NST, EDR, COV, PDR, FTI, LBR, ROH, ARD, FDR, and FRR, respectively. The experimental findings showed that TUBER was the more successful of the two routing methods that were examined. [16]

By using digital twin (DT) technology inside unmanned aerial vehicle (UAV) networks, this research investigates the developments of drones within the framework of sixth-generation mobile communication technology (6G) green Internet of Things (IoT), according to **Qi et al. (2023).** Using task manager scheduling, we provide a paradigm for green IoT UAV applications based on digital twins, in which separate tasks in the digital twin communicate with UAVs in the actual world. Using UAV-based 3D millimeter-wave radar imaging, we describe the DT's radio frequency (RF) characteristics. To take advantage of multipath reflections and reduce transmission energy, the wireless channel modelling emphasises the alignment of RF domains between the DT and the physical UAV. This alignment is based on ray tracing. In order to intelligently operate and maintain green UAV networks based on the Internet of Things, our numerical results have validated the effectiveness of the drone-enabled DT platform in attaining accurate RF representation of UAVs. [17]

In this study, **Ejiyeh (2024)** addresses the critical issues with 6G wireless communication networks by using UAVs' distinct characteristics. Innovative solutions are urgently needed due to the lofty 6G claims, including as ultra-low latency and ultra-reliable 1 Tbps data transfer. The integration of UAVs is prompted by the limits of traditional terrestrial base stations in situations that need ubiquitous connection. Despite their effectiveness, these limitations are apparent. We provide an all-encompassing answer to these problems. This requires UAVs to work together to obtain material from service providers, and then to set up secure connections with users so that information may be sent efficiently. For this reason, we provide two novel protocols: SeGDS, a method for group data downloading among UAVs; and SeDDS, a method for secure direct data sharing via out-of-band autonomous Device-to-Device (D2D) communication. These protocols provide lightweight, certificate-free solutions with characteristics like user revocation, non-repudiation, and mutual authentication by using certificateless signcryption and certificateless multi-receiver encryption. The suggested methods prioritise high availability and successfully identify free riding and Denial of Service (DoS) attacks. A comprehensive analysis highlights the efficiency and security advantages of the suggested protocols over current models; SeDDS reduces computation by 3x, making UAVs' communication loads lighter, and SeGDS satisfies the security needs of swarms of unmanned aerial vehicles (UAVs) by reducing communication costs by 4x while maintaining low computation costs. [18]

According to **Bajracharya et al. (2022),** one of the main objectives of 6G network architecture is to provide constant connection for devices and users regardless of the quality of the service they get. Furthermore, in order to provide dependable and low-latency access for the ever-changing quantity of mobile user devices, future 6G networks must be very versatile. Conversely, most existing base stations (BSs) and distant relay antennas are set up in predetermined geographic areas according to long-term traffic patterns, leaving limited room for re-deployment. Rigid radio access networks (RANs) can't keep everyone connected for 6G apps since data flows in both the space and time domains. Contrarily, cellular operators now have a once-in-a-lifetime chance to build airborne wireless infrastructure with the use of unmanned aerial vehicle (UAV) technology, which is known as wireless infrastructure UAV (WI UAV). WI UAV is capable of wireless communication and can self-stabilize to enhance end-user service quality, coverage, and spectrum efficiency. As a base station, relay, or data collector/disseminator, this study presents a 6G new radio in the unlicensed band (NR-U)-based WI UAV. Unmanned Aerial Vehicles (UAVs) are classified according to their features, functions, and uses. Moreover, this article delves into the many standardisation and regulatory efforts aimed at incorporating UAVs into the cellular network. We propose and describe a non-standalone NR-U network architecture for WI UAVs, talk about the design problems and prospects of NR-U for WI UAVs, and show you what the future holds for WI UAVs. [19]

Research on Wireless Sensor Networks (WSNs) assisted by Unmanned Aerial Vehicles (UAVs) has recently gained a lot of attention (**Liu et al., 2024**). Data transmission in UAV-WSNs relies on the routing protocol. To solve the problems with current routing protocols, such as excessive energy consumption and the early failure of some sensor nodes (SNs), we provide an effective protocol for UAV-WSNs data collecting. First, a model for UAV communication coverage is constructed, and the framework for collecting data from UAV-WSNs is set up. Secondly, we first split the routing region into two parts: one for air-to-ground and one for ground-to-ground, based on the data transmission connection. In light of this, we provide an unequal-sized clustering-based multi-hop routing protocol to encourage clusters to use energy in a balanced manner. Afterwards, we provide a sector dynamic adjustment method that takes its cues from lottery turntable wheels. This method simulates a rotation to dynamically alter the member nodes inside each cluster, ensuring that the energy consumption of each SN is well balanced. Finally, simulation and comparison experiments are used to verify the feasibility and efficiency of the suggested approach. [20]

A lot of people have been paying attention to UAV swarms recently (**Javed et al., 2024**) because of how well they can complete complex tasks. Increased intelligence, coordination, flexibility, survivability, and reconfigurability are all benefits of UAV swarms. A number of sub-systems, such as optimum trajectory planning, localization, task coordination, etc., must work together tightly since the system is multi-disciplinary.
Aspects such as swarm formation control, communication, swarm route planning, autonomy, coordination, and security are covered in this overview of UAV swarms. Furthermore, it delves into the latest technological developments in UAV swarm algorithms, which have enabled the creation of intricate UAV swarm systems. In addition to outlining potential military, civilian, and entertainment uses for UAV swarms, this article delves into their ethical considerations. In its last section, the article discusses the future of unmanned aerial vehicle swarm technology, the obstacles it may face, and the need of more study and development to fully use its capabilities. Ultimately, this research offers a thorough analysis of UAV swarm technology, discussing its capacity to transform several domains and bolster future progress. [21]

Providing wireless access in distant, disaster-stricken regions without communication infrastructure has garnered substantial interest, according to **Carvajal-Rodriguez et al. (2023),** since UAVs outfitted with communication technology provide a possible alternative. Still, a plethora of algorithms and technologies must be integrated to make UAVs capable of communications (like flying base stations) in practical situations. Particularly important for unmanned aerial vehicles (UAVs) operating alone or in networks is the development of 3D path planning algorithms that can identify the most obstacle-free routes that can cover a given area wirelessly. This work thoroughly examines current route-planning methods for UAVs in a 3D environment, taking into account that the majority of previous approaches only deal with 2D path planning. The solutions have used optimisation models, both optimum and heuristics. A search of the Scopus database yielded 37 articles out of 631 papers that are examined in this work. Along with the research goals and methods for the systematic mapping project, this article provides an overview of UAV-enabled communications systems. This study concludes with details on the 3D route planning problem's optimisation variables, algorithmic techniques, and the goals that should be minimised or maximised. [22]

According to **Xu et al. (2022),** the significance of wireless communication technology in the growth of national economies has been more significant in recent years. Natural catastrophes, public security crises, and other threats are only a few of the hazards and difficulties that individuals may encounter as a result of the rapid development of communication technology. Most of the time, long-term data traffic and user dispersion determine the deployment of traditional ground communication. It is not always possible to relocate infrastructure since it is often fixed. A critical component of public network communication is emergency communication. What this implies is that emergency procedures and means are combined and unified. Emergency services and emergency assistance are the responsibilities that need to be fulfilled. Expanding network coverage and improving network dependability are the main foci of this article. In the event that local networks are paralysed as a result of terrorist attacks or earthquakes, the creation of a rapid and reliable emergency communication network using both air and ground dimensions is also discussed. [23]

The Internet of Things (IoT), according to **Sharma and Mehra (2023),** has changed the world via its many uses in areas such as transportation, agriculture, home automation, and more. The Internet of Things (IoT) is revolutionising the way unmanned aerial vehicle (UAV) networks work. These networks bring together UAVs that are already in use and equip them with sensors, microcontrollers so they can share data, and a ground control station (GCS) that they can communicate with online. Surveillance, monitoring, payload delivery, and many other uses of UAV network systems based on the Internet of Things (IoT) produce a mountain of sensitive data that attackers in the middle may access. Potential security risks posed by jamming and eavesdropping attacks might compromise the communication between UAVs and GCS. Because their communication is not encrypted, UAV and GCS are both susceptible to mistakes. One such attack is GPS spoofing, which involves providing the UAV's controller erroneous coordinates. Despite a lot of work going into UAV security. Secure communication in UAV networks based on the Internet of Things is an area that needs more detailed evaluations. Finding and analysing peer-reviewed literature that covers topics like physical and logical attacks, proposed solutions like trajectory planning and lightweight schemes, blockchain-based solutions, quantum cryptography, etc., and published within the last six years is the goal of this paper. Using the study's approach as a framework, this article examines the UAV secure communication network and provides methodical answers to research issues. The report concludes with a number of points and suggestions for further study. [24]

Fathollahi et al. (2024), This study proposes a new architecture for the Internet of Things (IoT) networks that are powered by rotary-wing unmanned aerial vehicles (UAVs) and allow full-duplex (FD) wireless communication. In this setup, the UAV has an array of antennas for communication, whereas the randomly placed IoT sensors only have one antenna each. As a hybrid access point, the UAV charges the sensors and gathers data from them by transferring energy to them. Next, the sensors are grouped into N equal parts so that the UAV with MIMO technology can service each set of sensors during the whole period, which helps with energy optimisation and time management. By using the time division multiple access (TDMA) system to collect information from users, we provide a straightforward implementation of the wireless power transfer protocol in the sensors. That is to say, when the UAV flies over one set of sensors to another, or when it hovers over sensors in one set to another, the sensors in each set get energy from the UAV. When the UAV flies over each group, the sensors in each group relay data to the drone. Our two optimisation problems are the sum throughput maximisation and total time minimization issues, both of which are formulated under these assumptions. The numerical findings demonstrate that compared to the current networks, our ideal network offers superior performance. Compared to traditional networks, our innovative architecture actually uses more antennas to service more sensors [25].

In a recent study by **Yang et al. (2023),** the authors found that the proliferation of IoT communication devices has greatly improved people's daily lives. On the other hand, rescue efforts and the well-being of those impacted are profoundly damaged when communication infrastructure is destroyed during emergencies, which often causes interruptions in communication and makes it difficult to disseminate information. Key components of the answer to this problem have arisen as internet of things (IoT) big data analytics and unmanned aerial vehicle (UAV) technology. Internet of Things (IoT) big data analytics may aid decision-making during communication reconstruction after a catastrophe by assessing massive amounts of data from sensors, user actions, and data sent via networks. This allows for the forecast of communication demands in real-time and the development of strategies to optimise networks. A UAV-assisted communication coverage approach grounded on IoT big data analytics is proposed in this research, taking into consideration the specifics of post-disaster scenarios. Using unmanned aerial vehicles (UAVs) in a cruising mode, this approach divides the target region into several cells, each of which provides the bare minimum of data needed for user communication. Support for communication is selectively provided via flight-communication or hover-communication protocols, depending on the distribution patterns of users. A proposed algorithm called Inner Spiral Cruise Communication Coverage (IS-CCC) can optimise the UAV's flight speed while taking the mission's target area's coverage index, fairness index, and average energy efficiency into account. This algorithm can plan the UAV's cruising trajectory and achieve communication coverage without human intervention. This technique may reduce energy consumption in UAV-based communication, as shown in simulation findings, and enable energy-efficient cruise communication coverage in areas with complicated user distributions. [26]

A revolutionary shift in data collecting and communication systems has begun in a variety of fields with the integration of internet of things (IoT) technologies with unmanned aerial vehicles (UAVs), according to **Azadur et al. (2024).** This paper presents a novel effort that utilises the Pareto-based genetic ant colony optimisation (PGA) method to integrate multi-UAV route planning for integrated sensing and communication (ISAC) into ground-based CAT-M1 Internet of Things (IoT) sensor networks. Because of its speed, flexibility, and ability to incorporate domain knowledge smoothly, the PGA algorithm is very good in UAV route planning. We achieve multi-objective optimisation by minimising UAV travel distance and optimising energy consumption using the PGA algorithm. Improved situational awareness and real-time data collecting are made possible by a convex optimisation resource allocation technique, which works in tandem with ground-based IoT sensors and smooth UAV connectivity. In order to make the most efficient use of ground-based sensor data gathering, we have developed a UAV path planning PGA algorithm that allocates resources. With this innovative method, we are leading the charge to improve multi-UAV data gathering systems, which will lead to more efficient and resilient systems as well as game-changing solutions in many other fields. Impressively, the suggested ISAC system can reach throughputs of up to 95% of their capacity. [27]

The value of the Internet of Things (IoT) has grown in relation to fifth-generation (B5G) networks, according to **Xu (2023)**, thanks to developments in network slicing technology and the widespread use of intelligent gadgets. Disasters make communication more important and difficult since the main power source can become unstable and IoT devices might be insecure. In this research, we take into account UAVs as mobile base stations (BS) for the 5G mMTC network slicing emergency communication system in an effort to improve service quality. Efficiency in managing UAV trajectories, power consumption, and time slots are all improved by the proposed method. Optimising the UAV trajectory with different numbers of base stations is the first step. In the second stage, we apply the Dinkelbach method to the problem of non-convex fractional power allocation. We also create a system for distributing time slots that, by distributing them equitably among all users, improves the energy efficiency rating. Based on the idea of Markov Decision Processes (MDPs), the system model is then converted into a stochastic optimisation problem. We provide an approach for resource allocation based on Dueling-Deep-Q-Networks (DDQN) that maximises energy efficiency using the Reinforcement Learning (RL) technique. By solving the suggested sum-rate maximisation issue by optimising trajectories, allocating power, and allocating resources, the numerical results reveal that the efficiency of the UAV-based network and the base station has been substantially enhanced. Efficient optimisation reduces energy consumption by 1500 to 2200 joules while using fewer resources. [28]

The rapid advancement of 5G and beyond networks combined with UAVs has unleashed a plethora of new possibilities for various applications and state-of-the-art technologies, according to **Banafaa et al. (2024).** This has completely transformed the way digital connections, communications, and innovations take place. In this article, we take a look at all the angles of unmanned aerial vehicle (UAV) usage in 5G and beyond networks, including potential deployment scenarios, potential applications, new technology, regulations, research trends, and problems. A brief introduction and purpose set the stage for the systematic categorization of UAVs and the subsequent examination of pertinent literature. Both single- and multi-UAV setups are included in the survey. We provide the classification of UAV 5G applications and look into new innovation that may improve UAV communications. We talk about privacy, safety, spectrum allotment, and flying rules as they pertain to regulations. There is also a synopsis of important results and contributions, as well as illumination of current research trends and unresolved problems in the area, as well as the identification of encouraging avenues for future studies. Researchers, practitioners, and policymakers in the fields of unmanned aerial vehicles (UAVs) and communication will find this survey to be an invaluable resource. Better yet, it lays the groundwork for smart decision-making, encourages teamwork, and propels progress in unmanned aerial vehicle (UAV) and communication technology to meet the changing demands of our linked world. [29]

The cellular ground base station (GBS) is crucial for wireless communication, according to **Khan et al. (2024).** During catastrophes, whether natural or man-made, there might be a communication gap if the cellular GBS fails, even partly. Life, property, and the nation's infrastructure might be spared in such calamities by use of public safety communication (PSC). The PSC is able to provide vital communication and video transmission services to the impacted region during catastrophes. In particular, PSC services benefit from the mobility, flexibility, and ease of deployment offered by unmanned aerial vehicles (UAVs) operating as flying base stations (UAV-BSs). An observational UAV in this publication takes video feeds from AGUs in the impacted region and sends them to a nearby GBS via a relay UAV as part of a multi-UAV-assisted PSC network. The suggested research is to find the optimal path for the AGU-generated video streams to take in order to achieve maximum average utility once they reach the GBS. The goal is to maximise the efficiency of the system within the constraints imposed by the design of the system, which include the transmission rate, the probability of rate outages, the budget for transmit power, and the available bandwidth, all while optimising the positions of the observational and relay UAVs and the distribution of communication resources like bandwidth and transmit power. Therefore, a mathematical formulation of a simultaneous UAV deployment and resource allocation issue is provided. It will be quite difficult to find a solution to the given issue. A very effective iterative approach is suggested, taking into account the block coordinate descent and successive convex approximation methods. Lastly, we provide simulation results that demonstrate the superior performance of our suggested strategy compared to the current methodologies. [30]

Aiming to deliver seamless all-area, all-time coverage, space-air-ground integrated networks (SAGINs) have garnered great attention in light of the fast growth of 5G and 6G communications in recent years (**Lu et al., 2023**). In recent years, flying ad hoc networks (FANETs), which are an integral part of SAGINs, have seen extensive application in the transportation and agricultural industries. Efficient routing algorithms are necessary for SAGINs to ensure reliable communication. We examine the special communication design of FANETs in SAGINs in this research. Concurrently, we provide and group together preexisting routing methods. Furthermore, we survey the most recent developments in routing algorithm research throughout the last five years. By delving into the algorithms and drawing comparisons between the routing experiments and the features of UAVs, we conclude by elucidating the future directions of FANET routing algorithms in SAGINs research. [31]

According to **Al Amin et al. (2023),** the basic components of smart cities—the efficient and continuous electricity supply—depend on a smart grid that is in good working order. A faultless wireless communication system that offers secure, huge connection, low latency, flexibility, dependability, and adaptation to changing demands is necessary for smart grid operation management. This paper provides a current overview of how smart grids are making use of 6G wireless communication for their primary applications, particularly in the areas of highly connected and monitored systems, protected communication for managing operations and resources, and time-sensitive tasks. The essay begins by outlining the smart city's essential enablers and how the smart grid is essential to them. 6G wireless connectivity, smart grid technology, and smart cities are all laid forth in this study. Furthermore, the essay also expresses the reasons to include 6G wireless connectivity into the smart grid system. In order to fill a need in the existing literature, this study presents a review of the relevant literature and highlights its originality. In order to carry out the smart grid applications under consideration, we detail the innovative 6G wireless communication technologies. When compared to the previous generation of wireless communication system, the main performance metrics have been substantially enhanced by the novel technologies of 6G wireless communication. The modern overview of the principal uses of a 6G-served smart grid is a substantial portion of this text. Furthermore, this essay also discusses in detail the expected difficulties and intriguing avenues for future study. To learn more about how 6G wireless connectivity might improve smart grid applications and deal with new problems, this article is a great resource. [32]

3. Learning-based methods for solving optimization problems

Learning-based methods for solving optimization problems in signal processing algorithms for energy-efficient UAV-aided wireless communication networks encompass a wide range of techniques that adaptively improve performance with experience or data. These methods involve the application of various branches of artificial intelligence, such as machine learning and deep learning, to optimize signal processing tasks like resource allocation, routing, and power control to enhance energy efficiency.

Key methods include:

1. **Supervised Learning**: Using labeled data to train models that can predict future outcomes based on historical data. For UAV networks, this could mean predicting optimal flight paths or signal routing strategies that minimize energy consumption.
2. **Unsupervised Learning**: Finding hidden patterns or intrinsic structures in input data. Clustering algorithms, for example, could be used to group nearby devices for more efficient communication.
3. **Reinforcement Learning (RL)**: Learning to make decisions by taking actions in an environment to maximize a cumulative reward. RL can be used for dynamic decision-making in UAVs to adjust their paths or communication strategies in real-time for better energy savings.
4. **Deep Learning**: Leveraging neural networks with many layers (deep architectures) to model complex relationships in data. Convolutional neural networks might be employed for image and signal processing tasks related to UAV navigation and communication.
5. **Federated Learning**: A machine learning setting where the model is trained across multiple decentralized devices holding local data samples. This can be beneficial for UAV networks, where data privacy is essential, and the network's energy is preserved by avoiding the need to transmit large data sets.
6. **Transfer Learning**: Applying knowledge gained from solving one problem to a different but related problem. For UAVs, knowledge from one network's optimization could inform energy efficiency strategies in another network.
7. **Evolutionary Algorithms**: These are inspired by the process of natural selection and used for global optimization. They can be particularly useful for solving non-convex or complex optimization problems that arise in UAV path planning and resource allocation.

A. Neural Networks

1. **Signal Processing with Neural Networks**: Neural networks can be applied to various signal processing tasks such as noise reduction, channel estimation, and signal classification, which are crucial for maintaining the integrity of the communication signals in a UAV network.

2. **Energy Efficiency**: One of the significant challenges with UAVs is the limited energy available for long-duration flights. Neural networks can predict optimal flight paths, manage communication protocols, and adjust signal processing tasks in real-time to minimize energy consumption.

3. **Adaptive Algorithms**: NNs can adapt to changing network conditions (like node mobility, interference, and signal degradation) by learning from data. This adaptability is essential in dynamic environments where UAVs operate.

4. **Distributed Processing**: UAVs in a network can share the computational load of running neural networks, thus reducing the processing burden on individual UAVs and saving energy.

5. **Predictive Maintenance**: NNs can process data from UAV sensors to predict component failures before they occur, reducing downtime and saving energy by avoiding unnecessary flights.

6. **Communication Network Optimization**: By analyzing communication patterns, NNs can optimize the network topology, reducing the energy required for transmission and improving the overall efficiency of the wireless communication network.

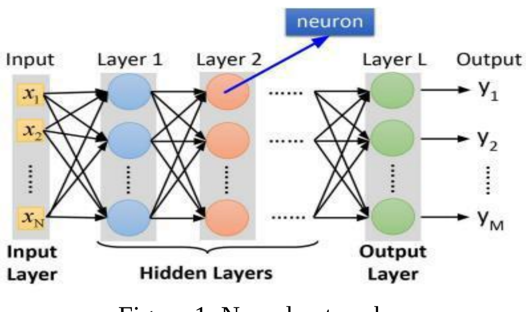

Figure 1. Neural networks

The figure 1 depicts a schematic representation of a multi-layered neural network architecture, which includes an input layer, multiple hidden layers, and an output layer. The input layer consists of 'N' nodes, each representing an input feature *xi*. The network comprises several hidden layers (Layer 1, Layer 2, ..., Layer L), with each layer containing a number of neurons. One neuron is highlighted in Layer 2, emphasizing its role in processing inputs from the previous layer through weighted connections. The hidden layers perform various transformations on the input data, extracting features and patterns necessary for learning tasks. The final layer, known as the output layer, contains 'M' nodes, each producing an output *yi*. This output represents the neural network's prediction or decision, based on the learned patterns from the input data. The architecture signifies a feedforward process, where data flows from the input to the output layer, and each neuron contributes to the form of learned representations at each stage, ultimately leading to the final output.

1) Perceptron Model

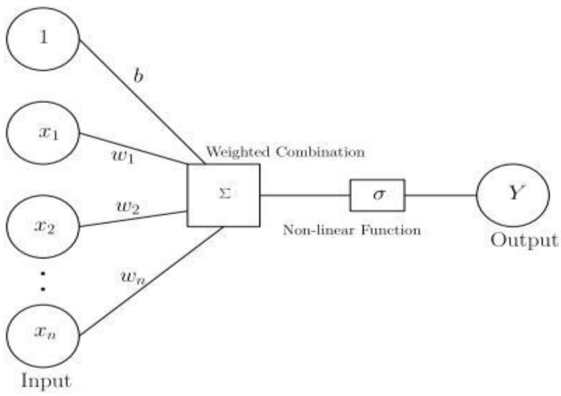

Figure 2. Fundamental workings of a single neuron

The figure 2 illustrates the fundamental workings of a single neuron within a neural network. Inputs $x1,x2,...,xn$ are fed into the neuron, each multiplied by a corresponding weight $w1,w2,...,wn$. Additionally, there is a bias term 'b' associated with the neuron. These inputs and bias are combined in a weighted sum, representing the weighted combination of inputs plus bias. This sum is then passed through a non-linear function denoted by σ, which is typically an activation function like a sigmoid, ReLU, or tanh. The activation function introduces non-linearity to the neuron's output, enabling the network to learn and model complex relationships. The result of the non-linear function is the output 'Y' of the neuron, which can then be used as an input to subsequent layers in a neural network or as a final output in the case of a single-layer network. This structure allows the neural network to perform complex mappings from inputs to outputs, forming the basis for tasks such as classification, regression, and more.

The Perceptron model is a type of artificial neuron originally proposed by Frank Rosenblatt in 1957. It's one of the simplest forms of a neural network, often used in binary classification problems (classifying inputs into one of two categories). Here's how the Perceptron model works:

1. **Input Values**: The Perceptron receives multiple input signals, each represented by numerical values. These inputs might represent different features of the data point being evaluated.
2. **Weights**: Each input is assigned a weight that represents its relative importance. Weights are adjusted during the learning process.
3. **Summation Function**: The Perceptron computes a weighted sum of the inputs.

$= \quad 11 + 22 + \cdots +$

where w_i is the weight and x_i is the input value.

4. **Activation Function**: The sum is then passed through an activation function to produce the output. In the case of the Perceptron, this is often a step function that outputs either 1 or 0:

$$= \int 1 \geq h \quad h \quad 0 \quad h$$

5. **Learning Rule**: The Perceptron is trained using the Perceptron learning rule, which updates the weights based on the error of the prediction. The rule is applied iteratively over the training set:

$= \quad + \Delta$

where $\Delta w_i = \eta(target - output)\, x_i$ and η is the learning rate, a small positive value that determines the size of the weight update.

6. **Bias**: Often, a bias term is added to the summation to allow the decision boundary to be offset from the origin.

The simplicity of the Perceptron makes it fast and efficient for certain tasks, but it also has limitations. For example, it can only classify data that is linearly separable, meaning the data can be separated into classes using a single straight line. It cannot solve non-linear problems, which led to the development of multi-layer networks and more complex learning algorithms capable of handling more complex tasks.

2) Backpropogation

Backpropagation for signal processing algorithms in energy-efficient UAVs (Unmanned Aerial Vehicles) aided wireless communication networks can significantly enhance performance and efficiency. Here's a breakdown of how backpropagation can be applied to this context:

1. **Optimizing Communication Protocols**: Backpropagation can be used to train neural networks that optimize UAV communication protocols, minimizing energy consumption while maximizing data transmission rates. By learning the most efficient pathways and signal processing methods, these networks can adapt to changing conditions, such as interference and signal attenuation, to maintain high-quality communication with minimal energy use.
2. **Adaptive Beamforming**: For UAVs utilizing beamforming techniques to focus the transmission and reception of signals, backpropagation can optimize the weights of the antenna arrays. This optimization can enhance the signal-to-noise ratio, leading to more efficient use of energy and improved communication range and quality.
3. **Dynamic Routing and Network Configuration**: In a UAV-aided wireless network, UAVs may act as mobile base stations or relay nodes. Backpropagation can help in dynamically adjusting the network configuration and routing protocols based on real-time data, such as UAV location, battery levels, and traffic demand, to ensure energy-efficient operation and maintain service quality.
4. **Signal Denoising and Interference Mitigation**: Backpropagation algorithms can train neural networks to perform advanced signal processing tasks, such as denoising and interference mitigation. By learning from past transmissions, these networks can effectively filter out noise and interference, reducing the power required to achieve clear communication.
5. **Predictive Maintenance and Energy Management**: Neural networks trained via backpropagation can predict system failures or identify suboptimal operation before they lead to significant energy waste. Predictive maintenance can ensure UAVs operate efficiently for longer periods, while energy management algorithms can make real-time decisions about power use, such as when to switch between communication modes or adjust transmission power based on the quality of service requirements.
6. **Learning and Adapting to Environmental Changes**: Backpropagation enables neural networks to learn from and adapt to environmental changes that affect signal propagation, such as weather conditions, obstacles, and varying landscapes. By continuously updating the model based on real-world operating conditions, UAV networks can maintain optimal performance without manual recalibration.

3) Deep Learning

Deep Learning for signal processing in energy-efficient UAVs (Unmanned Aerial Vehicles) aided wireless communication networks is a cutting-edge approach aimed at enhancing the capabilities and efficiency of such networks. This technique leverages deep neural networks (DNNs) to process complex signal data and make intelligent decisions, optimizing various aspects of UAV operation and communication. Here's an exploration of how deep learning can be applied to this domain:

1. **Channel Estimation and Modeling**: Deep learning models can be trained to accurately estimate and predict wireless communication channels' behavior. These models can handle non-linear and high-dimensional data, improving the reliability of UAV communications in dynamic environments. By accurately modeling the channel, UAVs can adapt their transmission power and modulation schemes to maintain efficient and robust communication links.

2. **Spectrum Sensing and Management**: Deep learning can significantly enhance spectrum sensing capabilities, enabling UAVs to identify and exploit available communication frequencies dynamically. This is particularly useful in crowded spectral environments or in scenarios where UAVs need to coexist with other wireless services without causing interference. By efficiently managing the spectrum, UAV networks can ensure high data rates and low-latency communications while conserving energy.

3. **Traffic Prediction and Network Optimization**: Deep learning algorithms can predict traffic patterns and optimize network resource allocation accordingly. This ensures that the UAV network can handle varying data demands efficiently, allocating bandwidth and energy resources where they are needed most, thereby improving the overall energy efficiency of the network.

4. **Energy-Efficient Routing**: UAVs often serve as aerial base stations or relay nodes in wireless networks. Deep learning models can optimize routing decisions based on the current network state, including UAV positions, battery levels, and data demands. By predicting the most energy-efficient routes for data packets, these models can significantly reduce the energy consumption of UAV networks.

5. **Signal Denoising and Enhancement**: Deep learning models excel at extracting useful information from noisy signals. In UAV communication networks, these models can be applied to denoise received signals, improving the quality of the communication even in adverse conditions. This capability allows UAVs to maintain reliable communication links without increasing the transmission power, thus saving energy.

6. **Anomaly Detection and Security**: Deep learning models can be trained to detect anomalies in communication patterns, identifying potential security threats or system malfunctions early. By addressing these issues promptly, UAV networks can avoid energy wastage due to malicious attacks or faulty operation.

7. **Adaptive Beamforming**: For UAV networks utilizing beamforming techniques, deep learning can optimize the beam patterns in real-time, focusing the energy in the desired directions while minimizing interference. This approach enhances communication quality and energy efficiency, especially in highly dynamic environments where conventional beamforming techniques may fall short.

The integration of deep learning into UAV-aided wireless communication networks represents a significant step forward in achieving high-efficiency, reliable, and intelligent communication systems. The ability of deep learning models to learn from data, adapt to new scenarios, and make optimized decisions in real-time makes them ideal for managing the complex and dynamic environments in which UAV networks operate. As research progresses, we can expect to see increasingly sophisticated applications of deep learning that push the boundaries of what's possible in UAV communications and signal processing.

B. FEATURES OF HARD OPTIMIZATION PROBLEMS

Hard optimization problems in the context of signal processing algorithms for energy-efficient UAVs (Unmanned Aerial Vehicles) aided wireless communication networks present several distinct features. These characteristics often make the optimization tasks computationally intensive and challenging to solve with traditional methods. Understanding these features is crucial for developing effective solutions. Here are some notable features of hard optimization problems in this context:

1. **High Dimensionality**: Many optimization problems in UAV networks involve high-dimensional parameter spaces. For example, optimizing the flight path for multiple UAVs while considering energy efficiency, signal coverage, and interference minimization involves a vast number of variables and constraints, leading to a high-dimensional optimization problem.

2. **Non-Convexity**: The objective functions in these problems are often non-convex, meaning they do not have a single global optimum. Instead, there may be many local optima, making it difficult to find the best solution. Non-convexity arises in problems like beamforming design, power allocation, and dynamic routing.

3. **Dynamic and Uncertain Environment**: UAV-aided networks operate in dynamic environments where factors such as UAV positions, energy levels, user demand, and channel conditions can change rapidly. The uncertainty and variability in these parameters

add complexity to the optimization problem, requiring adaptive and robust solutions.

4. **Multi-Objective Optimization**: Often, there is more than one objective to consider, such as maximizing network coverage, minimizing energy consumption, and ensuring reliable communication. These objectives can be conflicting, leading to a multi-objective optimization problem where trade-offs between different goals must be carefully balanced.

5. **Discrete and Continuous Variables**: The optimization problems can involve both discrete (e.g., selecting UAVs for specific tasks) and continuous variables (e.g., determining the optimal power level for signal transmission), adding another layer of complexity to finding a solution.

6. **Scalability Issues**: As the number of UAVs and users in the network increases, the size of the optimization problem grows exponentially. Scalability becomes a significant challenge, requiring efficient algorithms that can provide solutions within reasonable computational times.

7. **Interdependency of Variables**: The variables in these optimization problems are often interdependent. For example, the optimal position of a UAV can depend on the power allocation strategy, which in turn may affect and be affected by the routing protocol. This interdependency complicates the optimization process, as changes to one variable can have cascading effects on others.

8. **Constraints**: There are typically numerous constraints to consider, such as energy limitations, communication bandwidth, UAV flight regulations, and safety considerations. These constraints further limit the feasible solution space and add complexity to the optimization problem.

Addressing these features requires sophisticated optimization techniques, including machine learning and deep learning approaches, evolutionary algorithms, and other heuristic methods. These techniques can help navigate the challenges presented by hard optimization problems, providing efficient and practical solutions for enhancing the energy efficiency and performance of UAV-aided wireless communication networks.

1) RANDOMNESS

Incorporating randomness into signal processing algorithms for energy-efficient UAVs (Unmanned Aerial Vehicles) aided wireless communication networks can significantly enhance algorithm performance, particularly in dynamic and uncertain environments. Randomness can help in exploring the solution space more effectively, avoiding local optima, and adapting to changes in the network. Below is a stepwise algorithm that utilizes randomness in its operations:

Step 1: Initialization

- **1.1** Initialize the positions of UAVs randomly within the allowed airspace, ensuring they comply with safety regulations and operational constraints.
- **1.2** Randomly assign initial communication channels and power levels to each UAV, within the permissible ranges.

Step 2: Objective Function Evaluation

- **2.1** For the current UAV positions, channel assignments, and power levels, calculate the objective function. This function could measure network coverage, signal quality, energy consumption, or a combination of these and other factors.
- **2.2** Use randomness to introduce small perturbations in UAV positions, channel assignments, and power levels to evaluate potential improvements in the objective function.

Step 3: Solution Exploration

- **3.1** Employ a randomized algorithm, such as Simulated Annealing, Genetic Algorithm, and Particle Swarm Optimization, to explore the solution space. These algorithms use randomness to escape local optima and explore globally.
- **3.2** Update the positions of UAVs, channel assignments, and power levels based on the exploration results, following the algorithm's rules.

Step 4: Adaptation to Dynamic Changes

- **4.1** Monitor the environment for changes, such as user demand shifts, UAV energy levels, and channel conditions.
- **4.2** Introduce randomness to adjust UAV positions, channel assignments, and power levels dynamically, aiming to maintain or improve the network performance in response to these changes.

Step 5: Local Search and Optimization

- **5.1** Within the vicinity of the current solution, perform a local search using randomness to fine-tune UAV positions, channel assignments, and power levels.

- **5.2** Evaluate the objective function for these slightly varied solutions and adopt changes that lead to performance improvement.

Step 6: Convergence Check

- **6.1** Check if the algorithm has converged to a solution, which could be based on a set number of iterations, a target objective function value, or minimal changes in the objective function over several iterations.

- **6.2** If convergence criteria are met, proceed to Step 7. Otherwise, return to Step 3.

Step 7: Finalization and Deployment

- **7.1** Finalize the optimized UAV positions, channel assignments, and power levels.

- **7.2** Deploy the final configuration in the UAV-aided wireless communication network.

Step 8: Continuous Monitoring and Adjustment

- **8.1** Continuously monitor network performance and environmental conditions.

- **8.2** Periodically reintroduce randomness to adjust the network configuration, ensuring ongoing optimization in response to any changes.

2) MATHEMATICAL INTRACTABILITY AND COMPUTATIONAL COMPLEXITY

Addressing mathematical intractability and computational complexity in signal processing algorithms for energy-efficient UAVs (Unmanned Aerial Vehicles) aided wireless communication networks is crucial for designing efficient and practical systems. The following stepwise algorithm outlines a methodology to tackle these challenges, focusing on achieving an optimal balance between algorithmic performance and computational resources.

Step 1: Problem Formulation

- **1.1** Define the signal processing tasks (e.g., detection, estimation, filtering) and network objectives (e.g., energy efficiency, coverage, throughput).

- **1.2** Formulate the optimization problem, identifying variables, constraints, and the objective function, recognizing that the problem may be mathematically intractable due to its complexity or non-linearity.

Step 2: Complexity Analysis

- **2.1** Analyze the computational complexity of the formulated problem, identifying parts that contribute to intractability (e.g., NP-hardness, high dimensionality, non-convexity).

Step 3: Approximation and Heuristics

- **3.1** Develop and select approximation methods and heuristics that simplify the problem while retaining essential characteristics (e.g., greedy algorithms, local search methods).

- **3.2** Implement these approaches, ensuring they significantly reduce computational complexity without severely compromising solution quality.

Step 4: Decomposition and Modularity

- **4.1** Decompose the problem into smaller, more tractable modules that can be solved independently.

- **4.2** Solve each module using the most appropriate algorithms, considering trade-offs between performance and complexity.

Step 5: Algorithm Selection and Customization

- **5.1** Choose algorithms that are known to handle the specific types of complexity present in the problem efficiently (e.g., convex optimization for convex sub-problems, dynamic programming for problems with overlapping subproblems).

- **5.2** Customize these algorithms to the specific context of UAVs and wireless networks, incorporating domain knowledge to improve performance and reduce complexity.

Step 6: Exploit Parallelism and Distributed Computing

- **6.1** Identify opportunities for parallel processing, either within a single UAV's computing platform or across multiple UAVs and ground stations.

- **6.2** Implement parallel and distributed versions of the algorithms to leverage multiple processors and UAVs, reducing overall computation time.

Step 7: Iterative Refinement and Scalability

- **7.1** Employ iterative refinement techniques that start with coarse, approximate solutions and iteratively improve them, balancing computational load with solution accuracy.

- **7.2** Ensure that the algorithm scales well with the number of UAVs, the size of the area covered, and the complexity of the signal processing tasks.

Step 8: Performance Evaluation and Optimization

- **8.1** Evaluate the performance of the implementedalgorithmsinsimulated environments and real-world conditions, focusing on metrics such as computational time, energy efficiency, and the quality of signal processing.

- **8.2** Optimize the algorithms based on performance evaluations, adjusting parameters, and making refinements to improve efficiency and effectiveness.

3) LEARNING FOR HARD OPTIMIZATION PROBLEMS

Addressing hard optimization problems in signal processing for energy-efficient UAV (Unmanned Aerial Vehicles) aided wireless communication networks through learning involves developing adaptive, intelligent systems capable of handling complex, dynamic environments. The following steps outline a learning-based algorithmic approach to tackle these challenges effectively.

Step 1: Problem Definition and Decomposition

- **1.1 Define the Optimization Problem**: Clearly outline the hard optimization problem, including objectives (e.g., energy efficiency, signal coverage) and constraints (e.g., battery life, bandwidth).

- **1.2 Decompose Complex Problems**: Break down the overarching problem into smaller, more manageable sub-problems that can be addressed individually.

Step 2: Data Collection and Preprocessing

- **2.1 Gather Data**: Collect data relevant to the problem, such as signal characteristics, UAV positions, energy consumption rates, and environmental factors.

- **2.2 Preprocess Data**: Clean and preprocess the datatofacilitatelearning,including normalization, feature selection, and dimensionality reduction.

Step 3: Model Selection

- **3.1 Choose Learning Models**: Select appropriate machine learning or deep learning models based on the problem characteristics, such as neural networks, reinforcement learning.

- **3.2 Customize Models**: Tailor the chosen models to the specific aspects of the UAV network and signal processing tasks, considering the unique challenges and requirements.

Step 4: Feature Engineering and Representation Learning

- **4.1 Engineer Features**: Identify and engineer features that are most relevant to the optimization objectives and constraints.

- **4.2 Employ Representation Learning**: Use deep learning techniques to learn efficient representations of the data that capture the underlying patterns and dependencies related to the optimization problem.

Step 5: Learning and Optimization

- **5.1 Train Models**: Train the selected models on the preprocessed data, using historical data to learn the relationships between actions (e.g., UAV routing, power allocation) and outcomes (e.g., energy efficiency, signal quality).

Step 6: Incorporation of Domain Knowledge

- **6.1 Integrate Expert Knowledge**: Incorporate domain-specific knowledge into the learning process to guide the search space and improve learning efficiency.

- **6.2 Adaptive Learning**: Develop models that can adapt to new data and changing conditions, ensuring that the system remains effective over time.

Step 7: Validation and Testing

- **7.1 Cross-Validation**: Employ cross-validation techniques to evaluate the models' performance and avoid overfitting.

C. DEEP AND INTERACTIVE LEARNING TECHNIQUES

Deep and interactive learning techniques represent a cutting-edge approach in optimizing signal processing algorithms for energy-efficient UAVs (Unmanned Aerial Vehicles) aided wireless communication networks. By harnessing the power of deep learning, these techniques can automatically extract complex features and patterns from vast amounts of data, leading to more accurate and efficient signal processing methods. Interactive learning, or learning with human-in-the-loop, further enhances this by incorporating expert knowledge and feedback into the training process, enabling the models to adapt to nuanced scenarios and constraints not easily captured through data alone. Together, deep and interactive learning can significantly improve the adaptability and performance of UAV networks, optimizing resource allocation, reducing energy consumption, and enhancing communication reliability. These techniques allow for dynamic adjustment to changing network conditions, user demands, and environmental factors, ensuring optimal operation of the UAV network with minimal human intervention. The synergy between deep learning's capability to handle complex, high-dimensional data and interactive learning's adaptability to incorporate expert insights creates a robust framework for addressing the challenges of signal processing in energy-efficient UAV networks.

1) DEEP NEURAL NETWORKS (LSTM)

Implementing Deep Neural Networks, specifically Long Short-Term Memory (LSTM) networks, for signal processing in energy-efficient UAVs (Unmanned Aerial Vehicles) aided wireless communication networks involves several steps. These networks are particularly suited for processing time-series data or any data with temporal sequences, making them ideal for dynamic environments like UAV communications. Here's a stepwise approach:

Step 1: Problem Definition

- **1.1 Define the Signal Processing Task**: Identify the specific signal processing tasks (e.g., noise filtering, signal detection, prediction of signal quality) relevant to the UAV network.
- **1.2 Determine the Goals**: Specify the objectives, such as improving energy efficiency, enhancing signal quality, and minimizing latency.

Step 2: Data Collection and Preparation

- **2.1 Collect Data**: Gather temporal data relevant to the task, including signal measurements, UAV flight patterns, and environmental conditions.
- **2.2 Preprocess Data**: Clean and preprocess the data for training. This includes normalizing data, handling missing values, and possibly segmenting sequences into manageable sizes.

Step 3: Designing the LSTM Network

- **3.1 Select Network Architecture**: Decide on the configuration of the LSTM network, including the number of layers and the number of units in each layer.
- **3.2 Feature Selection**: Identify which features of the data will be used as inputs to the LSTM network.

Step 4: Training the LSTM Network

- **4.1 Split the Data**: Divide the data into training, validation, and test sets.
- **4.2 Define the Loss Function and Optimizer**: Choose a loss function that matches the objective of the signal processing task and an optimizer to update the network weights.
- **4.3 Train the Model**: Use the training data to train the LSTM network, adjusting weights to minimize the loss function. Employ the validation set to tune hyperparameters and prevent overfitting.

Step 5: Model Evaluation and Testing

- **5.1 Evaluate Performance**: Assess the model's performance using the test set and relevant metrics (e.g., accuracy for classification tasks, mean squared error for regression tasks).
- **5.2 Refine the Model**: Based on performance, refine the model by adjusting its architecture, tuning hyperparameters, or providing more training data.

2) RECURRENT NEURAL NETWORKS AND ECHO-STATE NETWORKS (ESNs)

Implementing Recurrent Neural Networks (RNNs) and Echo-State Networks (ESNs) for signal processing in energy-efficient UAVs (Unmanned Aerial Vehicles) aided wireless communication networks involves leveraging their unique capabilities to handle sequential data and dynamic environments. Here’s a stepwise algorithmic approach tailored for these networks:

Step 1: Problem Identification

- **1.1 Define Signal Processing Challenges**: Clearly identify the signal processing tasks needed for the UAV network, such as real-time signal filtering, prediction, or anomaly detection in communication signals.
- **1.2 Set Objectives**: Establish specific objectives like enhancing signal clarity, predicting network load, or reducing energy consumption for signal processing tasks.

Step 2: Data Collection and Preparation

- **2.1 Data Acquisition**: Gather historical and real-time data relevant to the UAV’s signal processing tasks, including signal strength, noise levels, and communication interruptions.
- **2.2 Preprocessing**: Standardize the data to a consistent format, normalize values, and possibly segment data into sequences suitable for RNN and ESN training.

Step 3: Selection of Network Type

- **3.1 Choose Between RNN and ESN**: Based on the task complexity and computational resources, decide whether a traditional RNN or an ESN is more appropriate. ESNs might be preferable for tasks requiring faster training times and fewer resources.

- **3.2 Define Architecture**: For RNNs, outline the layers and neurons. For ESNs, define the reservoir size and sparsity.

Step 4: Model Training and Development

- **4.1 Initialize Model Parameters**: For RNNs, initialize weights and biases. For ESNs, randomly generate the reservoir weights and define input and output weights.

- **4.2 Train the Model**: Use the prepared dataset to train the model. RNNs require backpropagation through time or variants thereof. ESN training involves adjusting the output weights based on the reservoir states.

Step 5: Model Optimization

- **5.1 Hyperparameter Tuning**: Experiment with different settings for learning rate, number of hidden units (for RNNs), reservoir size (for ESNs), and sparsity to find the optimal configuration.

- **5.2 Validation**: Use a separate validation dataset to evaluate the model and prevent overfitting.

Step 6: Evaluation and Testing

- **6.1 Performance Metrics**: Assess the model using appropriate metrics such as Mean Squared Error (MSE) for prediction tasks or accuracy for classification tasks.

- **6.2 Test on Real-World Data**: Evaluate the model's effectiveness on unseen real-world data to ensure it generalizes well beyond the training dataset.

3) Reinforcement Learning

Implementing Reinforcement Learning (RL) for signal processing in energy-efficient UAVs (Unmanned Aerial Vehicles) aided wireless communication networks involves training models to make decisions that maximize some notion of cumulative reward. This approach is particularly suited for dynamic environments where UAVs must adapt to changing conditions. Here's a stepwise algorithmic approach:

Step 1: Define the Environment

- **1.1 Identify State Space**: Define the state space that represents all possible situations the UAV network can encounter, including parameters like UAV positions, battery levels, signal quality, and environmental conditions.

- **1.2 Define Action Space**: Determine the set of actions available to the UAVs, such as adjusting positions, changing communication frequencies, and modifying power levels for signal transmission.

- **1.3 Outline Reward Structure**: Design a reward function that quantifies the success of taken actions, focusing on objectives like energy efficiency, signal coverage, and communication reliability.

Step 2: Select the Reinforcement Learning Model

- **2.1 Choose RL Algorithm**: Select an appropriate RL algorithm based on the problem complexity and available computational resources. Options include Q-learning, Deep Q-Networks (DQN), for continuous action spaces.

- **2.2 Define Model Architecture**: For deep RL, outline the neural network architecture that will approximate the policy (action selection) and value function (estimating future rewards).

Step 4: Training the RL Model

- **4.1 Initialize Parameters**: Start with random or heuristic-based parameters for the policy or value function models.

- **4.2 Interaction with Environment**: Let the RL agent interact with the environment by taking actions based on its current policy, observing the next state and reward, and updating its model accordingly.

- **4.3 Policy Update**: Use the collected experience (state, action, reward sequences) to update the policy and value function, aiming to maximize cumulative rewards.

Step 5: Model Evaluation and Refinement

- **5.1 Evaluate Performance**: Regularly test the RL agent's performance in the simulation environment using separate test scenarios not encountered during training.

- **5.2 Refinement**: Adjust the RL model, reward structure, or training process based on performance evaluations to improve outcomes.

4) Federated Learning

Federated Learning (FL) offers a decentralized approach to train machine learning models across multiple devices (or nodes) like UAVs (Unmanned Aerial Vehicles), without needing to share data centrally. This method is particularly advantageous for energy-efficient UAVs aided wireless communication networks, as it respects privacy, reduces communication overhead, and leverages distributed data. Here's a stepwise algorithmic approach to implement FL in this context:

Step 1: Define the Learning Task and Model

- **1.1 Specify the Signal Processing Task**: Clearly define the signal processing task(s) to be improved with FL, such as noise reduction, signal detection, and predictive maintenance.

- **1.2 Select a Model Architecture**: Choose a suitable machine learning model for the task, considering the computational constraints of UAVs.

Step 2: Initialize Federated Learning Environment

- **2.1 Deploy the Initial Model**: Distribute the initial model to all participating UAVs in the network. This model acts as the starting point for local training.

- **2.2 Establish Communication Protocol**: Set up a secure and efficient communication protocol for model updates exchange between the UAVs and the central server (if present).

Step 3: Local Model Training on UAVs

- **3.1 Collect Local Data**: Each UAV collects local signal processing data relevant to the defined task.

- **3.2 Train Locally**: Every UAV trains the shared model architecture on its collected data, adjusting the model weights to better perform the signal processing task based on local data.

Step 4: Model Aggregation

- **4.1 Aggregate Models**: After a predefined training period, model updates (weights or gradients) are sent to a central server and aggregated in a decentralized manner among UAVs, depending on the FL architecture.

- **4.2 Update Global Model**: Use an aggregation algorithm (e.g., Federated Averaging) to combine the local updates into an updated global model.

Step 5: Distribute the Updated Model

- **5.1 Broadcast Global Model**: The updated global model is distributed back to all participating UAVs.

- **5.2 Local Update**: Each UAV updates its local model with the new global model, synchronizing the learning across the network.

Step 6: Iteration and Convergence

- **6.1 Repeat Training Cycles**: Steps 3 through 5 are repeated for multiple rounds until the model converges or meets the performance criteria.

- **6.2 Monitor Convergence**: The central server or a designated UAV monitors the learning progress and convergence of the global model.

Table 1. Summary table of when to utilize each learning-based technique in solving optimization problems.

Technique	Problem type	Main Feature
LSTM	Unknown objective, constraint	Pattern detection
ESN	Classification and regression predication problems	Sequence and pattern detection
RL	Predicition problems, NP-hard Problems	Active learning
FL	Excessive data, privacy concerns	Local training

The table summarizes various techniques applied to different problem types in signal processing algorithms for energy-efficient UAVs aided wireless communication networks, highlighting their main features:

- **Long Short-Term Memory (LSTM)** networks are suited for scenarios with unknown objectives or constraints, excelling in pattern detection within data sequences. Their ability to remember information over long periods makes them ideal for complex signal processing tasks where patterns unfold over time.

- **Echo-State Networks (ESN)** are primarily used for classification and regression prediction problems. Like LSTMs, ESNs are adept at sequence and pattern detection but are particularly noted for their efficient training processes, making them suitable for tasks where rapid model adaptation is required.

- **Reinforcement Learning (RL)** is applied to prediction problems and NP-hard problems, featuring active learning as its main characteristic. RL algorithms learn optimal policies through trial and error, adjusting actions based on rewards to solve problems where direct solutions are computationally infeasible.

- **Federated Learning (FL)** addresses challenges related to excessive data and privacy concerns by enabling local training on devices. It is particularly relevant in scenarios where data cannot be centralized due to privacy or bandwidth constraints, allowing models to learn from distributed data sources without compromising user privacy.

Each technique offers unique advantages for specific problem types within UAV networks, from pattern detection in temporal data to privacy-preserving distributed learning, showcasing the diversity of approaches in optimizing signal processing for enhanced network efficiency and effectiveness.

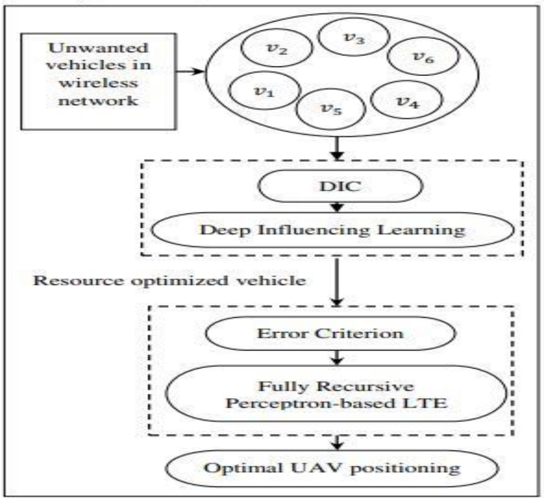

Figure 3. Block Diagram of Fully Recursive Long Short Term Memory (FR-LSTM) Method

The figure 3 presents a layered approach for optimizing UAV positioning in a wireless network cluttered with unwanted vehicles. It begins with the identification of unwanted vehicles in the network, utilizing a process designated as DIC (possibly "Detection of Intruding Cars" or a similar concept). The information gleaned from DIC feeds into a "Deep Influencing Learning" system, which likely uses deep learning techniques to understand and mitigate the influence of these vehicles on network performance. Subsequently, this process optimizes resources for a "Resource optimized vehicle," which could refer to the UAV or a dedicated vehicle within the network responsible for efficient resource management. The next stage involves an "Error Criterion" that evaluates the performance and accuracy of the system, feeding into a "Fully Recursive Perceptron-based LTE" algorithm. This suggests a learning mechanism that uses perceptron models, potentially to adaptively fine-tune LTE (Long-Term Evolution) communication parameters. The culmination of this process is the "Optimal UAV positioning," indicating that the system's output is the ideal placement of UAVs to ensure efficient network operation despite the presence of unwanted vehicles. This approach signifies a comprehensive system aimed at maintaining robust wireless network performance through adaptive learning and strategic placement of UAVs.

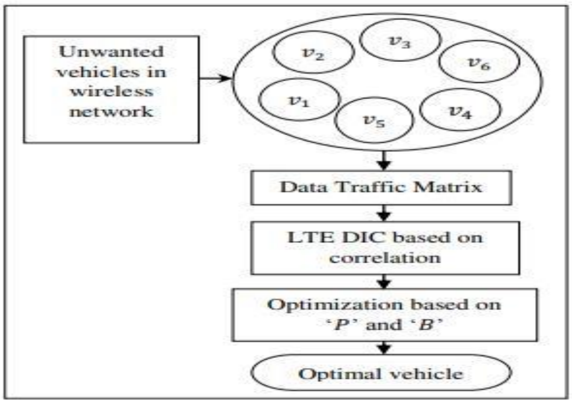

Figure 4. Block Diagram of Deep Influencing Learning-based LTE Model

The provided figure 4 outlines a framework for addressing the issue of unwanted vehicles in a wireless network, aiming to achieve optimal vehicle performance. Initially, the network identifies unwanted vehicles, which could be non-authorized users or potential sources of interference. This information is then processed to create a Data Traffic Matrix, likely capturing the communication patterns and traffic caused by these vehicles. The next stage involves LTE DIC (which could stand for "Detection, Identification, and Cancellation") based on correlation, suggesting a method to detect and mitigate interference or unauthorized access by analyzing the correlation within the data traffic. Following this, an optimization process is applied, which considers parameters 'P' and 'B'—potentially referring to power and bandwidth, or other network resources. The ultimate goal of this process is to determine the Optimal vehicle, which could be the best configuration or positioning of an authorized vehicle in the network to ensure efficient and secure communication. This systematic approach emphasizes data-driven decision-making to maintain network integrity and performance.

4. Experimental results and discussion

4.1 Simulation setup involves a wireless network

Table 2. Simulation setup involves a wireless network

Simulation Parameter	**Value**
Network area	2000m * 2000m
Number of unmanned vehicles	50, 100, 150, 200, 250, 300, 350, 400, 450, 500
Vehicle distribution	Uniform random
Initial energy in each unmanned vehicle	4J
Control packet size	64bytes
Data packet size	1024bytes
Simulation time	100s

Pause time	20s
Mobility model	Random Way Point
Transmission range	500m
Number of runs	20
UAV-UAV range	300m
UAV-Ground range	300m
Propagation mode	Free space
Trans/Receive antenna	Omnidirectional
Medium Access Control	Time Division Multiple
(MAC) protocol	Access (TDMA)
Constant Bit Rate (CBR)	512 bytes
UAV-UAV link bandwidth	5 Mbps
UAV-Ground link	10 Mbps
Packet Type	UserDatagramProtocol (UDP)
Channel Type	Wireless
Wi-Fi version	802.11b

This simulation setup table 2 involves a wireless network over a 4 square kilometer area, testing various numbers of unmanned vehicles (UAVs) from 50 to 500, distributed randomly. Each UAV starts with an energy reserve of 4 Joules. The simulation sends control packets of 64 bytes and data packets of 1024 bytes over a 100-second simulation period, with a 20-second pause. The mobility is modeled using a Random Way Point model with a 500-meter transmission range. Twenty simulation runs are conducted to ensure statistical relevance. Communication is facilitated through a Time Division Multiple Access (TDMA) protocol with omnidirectional antennas, and data is transmitted at a constant bit rate of 512 bytes. The UAV-to-UAV and UAV-to-ground communication ranges are set to 300 meters with bandwidths of 5 Mbps and 10 Mbps, respectively, using the User Datagram Protocol (UDP) over a wireless channel and conforming to the 802.11b Wi-Fi standard.

4.2 Result and discussion

Table 3. Packet delivery ratio

No of Nodes	50	100	150	200	250
INSBCA	70	75	78	78	78
TEEN	75	78	78	78	79
PEGASIS	81	85	85	86	87
EEMDCHSP	85	86	85	88	89
ML-SOPCSPRP	98	98	97	98	98

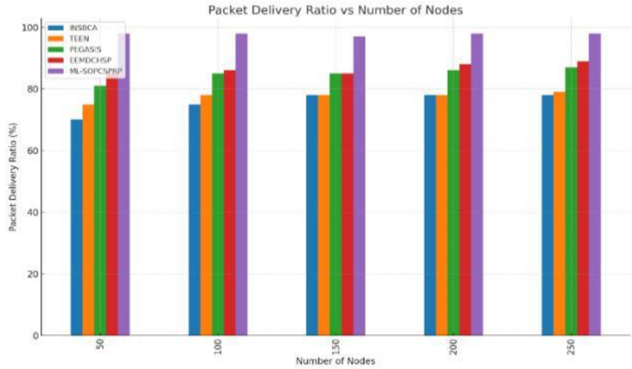

Figure 5. Packet delivery ratio

The table 3 and figure 5 presents packet delivery ratios for various routing protocols across different numbers of network nodes. As the number of nodes increases from 50 to 250, the Intersect Node Selection Based Clustering Algorithm (INSBCA) shows slight improvement from 70% to 78%. The Threshold-sensitive Energy-Efficient sensor Network protocol (TEEN) performs similarly, starting at 75% and increasing to 79%. The Power-Efficient Gathering in Sensor Information Systems (PEGASIS) and the Energy Efficient and Mobility-based Dynamic Cluster Head Selection Routing Protocol (EE-MDCHSRP) show more substantial improvements, with PEGASIS going from 81% to 87% and EE-MDCHSRP from 85% to 89%. The Machine Learning-Based for Solving Optimization Problems in Communications and Signal Processing routing protocol (ML-SOPCSPRP) consistently outperforms the others, maintaining a high packet delivery ratio of 97% to 98% regardless of the number of nodes.

Table 4. End-to-end delay (ms)

No of Nodes	50	100	150	200	250
INSBCA	0.7	0.7	0.7	0.8	0.8
TEEN	0.4	0.6	0.6	0.7	0.7
PEGASIS	0.2	0.3	0.4	0.3	0.4
EEMDCHSP	0.1	0.1	0.2	0.2	0.2
ML-SOPCSPRP	0.01	0.02	0.02	0.03	0.3

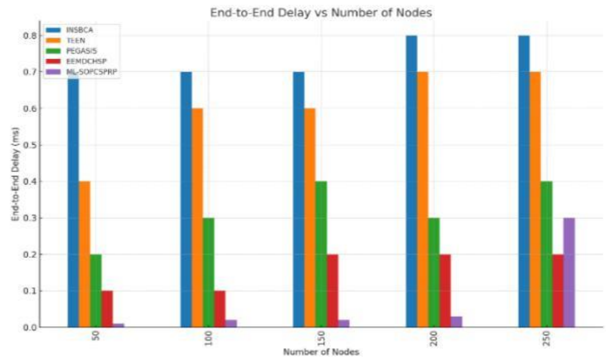

Figure 6. End-to-end delay (ms)

The table 4 and figure 6 of the end-to-end delay in milliseconds across different numbers of nodes for various routing protocols is as follows: INSBCA shows a consistent delay of 0.7 ms for 50 to 150 nodes, which slightly increases to 0.8 ms for 200 to 250 nodes. TEEN starts with a delay of 0.4 ms for 50 nodes and gradually increases to 0.7 ms as the number of nodes reaches 250. PEGASIS demonstrates the best performance among the traditional protocols with a delay starting at 0.2 ms for 50 nodes and fluctuating slightly between 0.3 ms and 0.4 ms for up to 250 nodes. EEMDCHSP maintains the lowest delay among them, starting at 0.1 ms for 50 to 100 nodes and only marginally increasing to 0.2 ms as the network size grows. ML-SOPCSPRP outperforms all with an impressively low delay, beginning at 0.01 ms for 50 nodes and only rising to 0.03 ms for 200 nodes, but showing a significant increase to 0.3 ms for 250 nodes.

Table 5. Throughput (%)

No of Nodes	**50**	**100**	**150**	**200**	**250**
INSBCA	93	92	91	89	85
TEEN	94	94	93	91	89
PEGASIS	95	94	93	92	91
EEMDCHSP	97	96	95	94	93
ML-SOPCSPRP	98	98	97	96	96

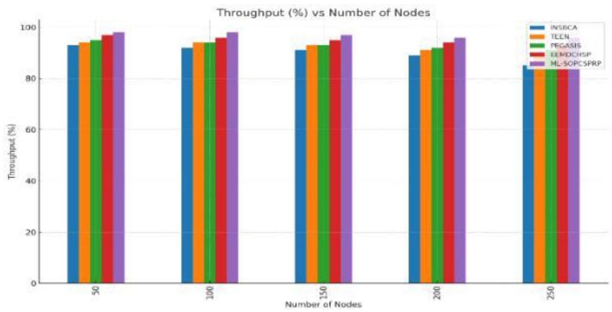

Figure 7. Throughput (%)

The table 5 and figure 7 provided data reflects the throughput performance of various network protocols across different numbers of nodes. The throughput decreases as the number of nodes increases for each protocol. INSBCA starts with 93% throughput for 50 nodes and drops to 85% for 250 nodes. TEEN and PEGASIS also show a declining trend, with TEEN dropping from 94% to 89%, and PEGASIS from 95% to 91%. EEMDCHSP starts at 97% for 50 nodes and reduces to 93% for 250 nodes. ML-SOPCSPRP maintains the highest throughput, starting at 98% and only slightly declining to 96% as the number of nodes increases. This indicates that while all protocols experience a reduction in throughput as the network scales up, ML-SOPCSPRP remains the most efficient throughout.

Table 6. Network lifetime (Sec)

NO of Nodes	50	100	150	200	250
INSBCA	80	79	78	77	76
TEEN	83	82	81	79	78
PEGASIS	85	84	83	82	81
EEMDCHSP	89	88	86	85	84
ML-SOPCSPRP	92	92	91	90	90

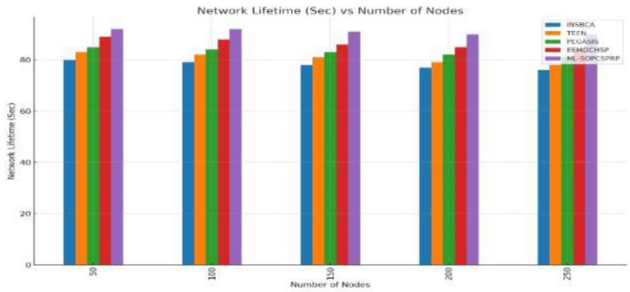

Figure 8. Network lifetime (Sec)

The table 6 and figure 8 data presents the network lifetime in seconds of different routing protocols with an increasing number of nodes from 50 to 250. INSBCA shows a decreasing lifetime from 80 to 76 seconds, indicating a decline as the network grows. TEEN displays slightly better longevity, starting at 83 seconds and reducing to 78 seconds with the increase of nodes. PEGASIS provides a more stable lifetime ranging from 85 to 81 seconds. EEMDCHSP outperforms the previous with lifetimes from 89 down to 84 seconds, suggesting efficient energy usage. ML-SOPCSPRP offers the highest and most stable network lifetimes, maintaining 92 seconds up to 100 nodes and only decreasing to 90 seconds at 250 nodes, reflecting optimal performance in terms of network longevity.

Table 7. Energy consumption (J)

NO of Nodes	**50**	**100**	**150**	**200**	**250**
INSBCA	24	23	22	21	21
TEEN	18	19	19	20	20
PEGASIS	17	16	15	14	14
EEMDCHSP	15	13	14	12	13
ML-SOPCSPRP	12	12	12	11	11

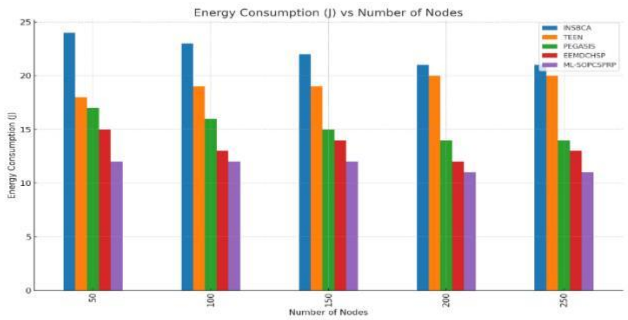

Figure 8. Energy consumption (J)

The table 7 and figure 9 provided data illustrates the energy consumption in Joules of various routing protocols across networks of different sizes, ranging from 50 to 250 nodes. INSBCA's energy consumption slightly decreases from 24J to 21J as the number of nodes increases, indicating a conservative energy profile at larger scales. TEEN starts with a lower consumption of 18J at 50 nodes and gradually increases to 20J as the network size grows to 250 nodes. PEGASIS demonstrates a more efficient energy use, starting at 17J and decreasing to 14J with the addition of more nodes, showing better energy management with scale. EEMDCHSP shows an irregular pattern but maintains a low energy use, ranging between 15J and 12J. ML-SOPCSPRP exhibits the most energy-efficient pattern, maintaining a consistent consumption of 12J up to 150 nodes and reducing further to 11J at larger sizes, thus showing the highest energy efficiency among the protocols tested.

Table 8. Overall performance

	INSBCA	TEEN	PEGASIS	EEMDCHSP	ML-SOPCSPRP
Accuracy(%)	87	89	91	93	98

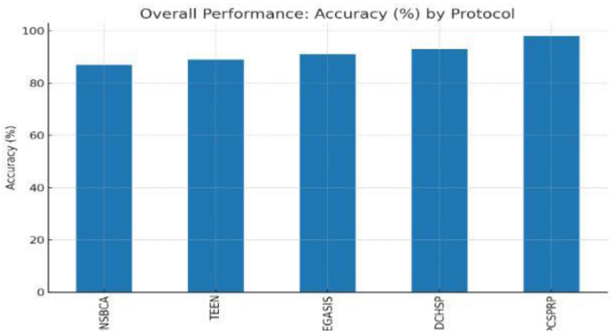

Figure 9. Overall performance

The table 8 and figure 9 data represents the overall performance of various routing protocols, measured by their accuracy percentage. INSBCA has an accuracy of 87%, indicating a moderate level of precision. TEEN slightly improves on this, achieving an 89% accuracy rate. PEGASIS further increases the accuracy to 91%, while EEMDCHSP stands at 93%, showing a high degree of accuracy. ML-SOPCSPRP tops the chart with an impressive 98% accuracy, indicating the highest level of performance among the protocols listed.

Table 9. Impact of Root Mean Square Error (%)

NO of Nodes	50	100	150	200	250
INSBCA	3.4	3.6	3.8	3.9	4.3
TEEN	2.5	2.6	2.8	2.9	2.9
PEGASIS	1.2	1.3	1.4	1.6	1.8
EEMDCHSP	0.8	0.89	0.9	0.94	0.99
ML-SOPCSPRP	0.2	0.25	0.29	0.35	0.39

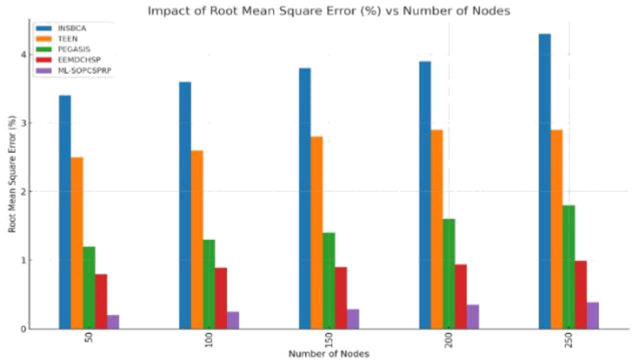

Figure 10. Impact of Root Mean Square Error (%)

The table 9 and figure 10 shows the impact of Root Mean Square Error (RMSE) as a percentage across five routing protocols with increasing network sizes, from 50 to 250 nodes. INSBCA's RMSE rises from 3.4% to 4.3%, suggesting a degradation in accuracy as the network expands. TEEN maintains a lower RMSE, starting at 2.5% and slightly increasing to 2.9%, which indicates a moderate impact on accuracy with scaling. PEGASIS demonstrates a better performance with a lower starting RMSE of 1.2% and a gentle rise to 1.8%, reflecting a stable accuracy profile. EEMDCHSP shows even greater accuracy with RMSE starting at 0.8% and gradually increasing to just below 1%. ML-SOPCSPRP stands out with the lowest RMSE, beginning at 0.2% and marginally increasing to 0.39%, showcasing the highest accuracy and least impact from scaling within the tested protocols.

Table 10. Latency milliseconds (ms)

No of Nodes	50	100	150	200	250
INSBCA	5.2	6.3	7.4	8.4	9.1
TEEN	4.3	4.6	4.8	5.2	5.6
PEGASIS	3.7	3.9	4.2	4.5	5
EEMDCHSP	2.4	3.1	3.4	4	4.3
ML-SOPCSPRP	1	2	2.5	3.8	4

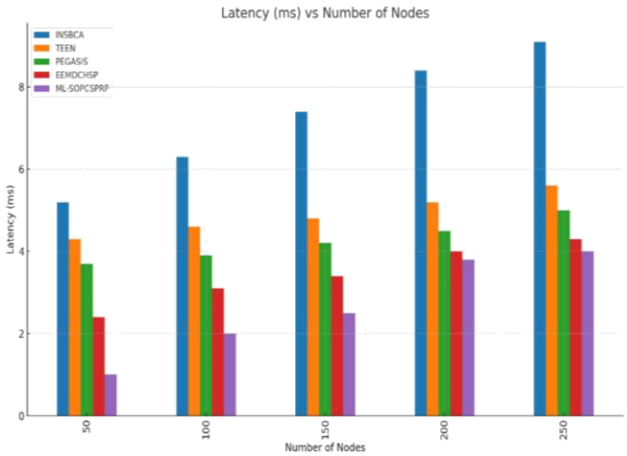

Figure 11. Latency milliseconds (ms)

The table 10 and figure 11 data depicts latency in milliseconds for different numbers of nodes using five routing protocols. With INSBCA, latency worsens as nodes increase, starting at 5.2 ms for 50 nodes and rising to 9.1 ms for 250 nodes. TEEN maintains lower latency, beginning at 4.3 ms and reaching 5.6 ms, suggesting better scalability. PEGASIS offers improved latency, starting at 3.7 ms and moderately increasing to 5 ms. EEMDCHSP shows significant efficiency with latency starting as low as 2.4 ms and only rising to 4.3 ms. ML-SOPCSPRP demonstrates the lowest latency figures, starting at an impressive 1 ms for 50 nodes and only climbing to 4 ms for 250 nodes, indicating it's highly effective in maintaining low latency even as the network size increases.

5. Conclusion

The application of various machine learning and signal processing techniques to optimize UAV-aided wireless communication networks, it is evident that each method brings distinct advantages to address complex challenges. The LSTM excels in pattern detection for problems with unknown objectives or constraints, leveraging its capacity for long-term dependency modeling. Echo-State Networks (ESNs) offer efficient training for sequence and pattern detection, making them suitable for classification and regression prediction problems. Reinforcement Learning (RL) stands out in actively learning from interactions with the environment, effectively navigating prediction and NP-hard problems through a system of rewards. Federated Learning (FL) emerges as a particularly innovative approach, enabling local training across distributed networks, addressing excessive data and privacy concerns. By processing data locally and only sharing model updates, FL ensures privacy and reduces the need for extensive data transmission, which is crucial for energy-constrained UAV networks. The integration of FL within the framework for optimizing the performance of UAVs in wireless networks was further explored. It starts with unwanted vehicles' identification and mitigation through a Data Traffic Matrix, progressing to LTE DIC based on correlation, followed by optimization techniques tailored to the network's specific 'P' and 'B' parameters, culminating in the determination of the optimal vehicle within the network. The diagrammatic representation of a neural network's architecture emphasizes the importance of structure in machine learning. A multi-layered network, with its input, hidden, and output layers, enables the learning of complex functions, with each neuron contributing to the overall decision-making process. The schematic detailing the operation of a single neuron within a network showcases the fundamental process of information transformation in neural networks. Inputs are weighted and combined, then passed through a non-linear function, resulting in the output. This process is at the core of neural networks' ability to model complex, non-linear relationships. The sequential examination of these techniques and models, we gain a comprehensive insight into the multifaceted strategies for enhancing signal processing in UAV networks. Each method contributes to the overarching goal of achieving efficient, robust, and secure wireless communication facilitated by UAVs, with the final aim of optimizing UAV positioning to ensure an effective network operation. This holistic approach underscores the synergy between different machine learning strategies and the complex requirements of contemporary wireless communication networks.

Acknowledgments

Mahesh Y Sumthane: Conceptualization, Methodology, Software, Field study, Data curation, Writing-Original draft preparation, Validation. **Dr. Kirti Saraswat:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] Maheswar, Rajagopal, Murugan Kathirvelu, and Kuppusamy Mohanasundaram. "Energy Efficiency in Wireless Networks." Energies 17, no. 2 (2024): 417.

[2] Jeganathan, Anandpushparaj, Balaji Dhayabaran, Dushantha Nalin K. Jayakody, Sanjaya Arunapriya Ranchagodage Don, and P. Muthuchidambaranathan. "An intelligent age of information based self-energized UAV-assisted wireless communication system." *IET Communications* 17, no. 19 (2023): 2141-2151.

[3] Rose, JT Anita, C. A. Subasini, F. Sangeetha Francelin Vinnarasi, and S. P. Karuppiah. "Power allocation for enhancing energy efficiency in

unmanned aerial vehicle networks." *International Journal of Communication Systems* (2024): e5662.
[4] Ghamari, Mohammad, Pablo Rangel, Mehrube Mehrubeoglu, Girma S. Tewolde, and R. Simon Sherratt. "Unmanned aerial vehicle communications for civil applications: A review." *IEEE Access* 10 (2022): 102492-102531.
[5] Massaoudi, Ayman, Abdelwahed Berguiga, Ahlem Harchay, Mossaad Ben Ayed, and Hafedh Belmabrouk. "Spectral and energy efficiency trade-off in UAV-based olive irrigation systems." *Applied Sciences* 13, no. 19 (2023): 10739.
[6] Gupta, Akshita, and Sachin Kumar Gupta. "A survey on green unmanned aerial vehicles-based fog computing: Challenges and future perspective." *Transactions on Emerging Telecommunications Technologies* 33, no. 11 (2022): e4603.
[7] Alkanhel, Reem, Ahsan Rafiq, Evgeny Mokrov, Abdukodir Khakimov, Mohammed Saleh Ali Muthanna, and Ammar Muthanna. "Enhanced Slime Mould Optimization with Deep-Learning-Based Resource Allocation in UAV-Enabled Wireless Networks." *Sensors* 23, no. 16 (2023): 7083.
[8] Luo, Yixin, and Gui Fu. "UAV based device to device communication for 5G/6G networks using optimized deep learning models." *Wireless Networks* (2023): 1-15.
[9] El-Gayar, Mostafa Mahmoud, and Mohammed Nasser Ajour. "Resource Allocation in UAV-Enabled NOMA Networks for Enhanced Six-G Communications Systems." *Electronics* 12, no. 24 (2023): 5033.
[10] Alharbi, Hatem A., Barzan A. Yosuf, Mohammad Aldossary, Jaber Almutairi, and Jaafar MH Elmirghani. "Energy Efficient UAV-Based Service Offloading Over Cloud-Fog Architectures." *IEEE Access* 10 (2022): 89598-89613.
[11] Alnakhli, Mohammad, Ehab Mahmoud Mohamed, Wazie M. Abdulkawi, and Sherief Hashima. "Joint User Association and Power Control in UAV Network: A Graph Theoretic Approach." *Electronics* 13, no. 4 (2024): 779.
[12] Abdel-Basset, Mohamed, Reda Mohamed, Ibrahim Alrashdi, Karam M. Sallam, and Ibrahim A. Hameed. "Evolution-based energy-efficient data collection system for UAV-supported IoT: Differential evolution with population size optimization mechanism." *Expert Systems with Applications* 245 (2024): 123082.
[13] Ding, Xufei, Wen Tian, Guangjie Liu, and Xiaopeng Ji. "Energy Consumption Minimization in Unmanned Aerial Vehicle-Enabled Secure Wireless Sensor Networks." *Sensors* 23, no. 23 (2023): 9411.
[14] Sugesh, M. S., and G. Vairavel. "Systematic Literature Review on the Machine Learning Techniques for UAV-Assisted mm-Wave Communications." In *International Conference on Electrical and Electronics Engineering*, pp. 517-534. Singapore: Springer Nature Singapore, 2023.
[15] Chen, Xiaomin, Qinbin Zhou, Zhiheng Wang, Qiang Sun, and Miaomiao Xu. "Reliable and energy-efficient UAV-assisted air-to-ground transmission: Design, modeling and analysis." *Computer Communications* 204 (2023): 66-77.
[16] Bouchekara, Houssem REH, Abdulazeez F. Salami, Yusuf A. Sha'aban, Mouaaz Nahas, Mohammad S. Shahriar, and Mohammed A. Alanezi. "TUBER: Time-aware UAV-based energy-efficient reconfigurable routing scheme for smart wireless livestock sensor network." *Plos one* 19, no. 1 (2024): e0292301.
[17] Qi, Fei, Weiliang Xie, Lei Liu, Tao Hong, and Fanqin Zhou. "UAV Digital Twin Based Wireless Channel Modeling for 6G Green IoT." *Drones* 7, no. 9 (2023): 562.
[18] Ejiyeh, Atefeh Mohseni. "Secure, Robust, and Energy-Efficient Authenticated Data Sharing in UAV-Assisted 6G Networks." *arXiv preprint arXiv:2402.11382* (2024).
[19] Bajracharya, Rojeena, Rakesh Shrestha, Shiho Kim, and Haejoon Jung. "6G NR-U based wireless infrastructure UAV: Standardization, opportunities, challenges and future scopes." *IEEE Access* 10 (2022): 30536-30555.
[20] Liu, Hao, Renwen Chen, Shanshan Ding, Zihao Jiang, Fei Liu, and Junyi Zhang. "An energy efficiency routing protocol for UAV-aided WSNs data collection." *Ad Hoc Networks* 154 (2024): 103378.
[21] Javed, Sadaf, Ali Hassan, Rizwan Ahmad, Waqas Ahmed, Rehan Ahmed, Ahsan Saadat, and Mohsen Guizani. "State-of-the-Art and Future Research Challenges in UAV Swarms." *IEEE Internet of Things Journal* (2024).
[22] Carvajal-Rodriguez, Jorge, Marco Morales, and Christian Tipantuña. "3D path planning algorithms in UAV-enabled communications systems: a mapping study." *Future Internet* 15, no. 9 (2023): 289.
[23] Xu, Zhenyu, Jinfang Li, and Xun Xu. "Research on Emergency Communication Technology of UAV Based on D2D." In *International Conference on 5G for Future Wireless Networks*, pp. 84-99. Cham: Springer Nature Switzerland, 2022.
[24] Sharma, Jatin, and Pawan Singh Mehra. "Secure communication in IOT-based UAV networks: A systematic survey." *Internet of Things* (2023): 100883.
[25] Fathollahi, Leyla, Mahmood Mohassel Feghhi, and Mahmoud Atashbar. "Energy optimization for full-duplex wireless-powered IoT networks using rotary-wing UAV with multiple antennas." *Computer Communications* 215 (2024): 62-73.
[26] Yang, Biao, Xuanrui Xiong, He Liu, Yumei Jia, Yunli Gao, Amr Tolba, and Xingguo Zhang. "Unmanned Aerial Vehicle Assisted Post-Disaster Communication Coverage Optimization Based on Internet of Things Big Data Analysis." *Sensors* 23, no. 15 (2023): 6795.
[27] Azadur, Rahman Md, Chaitali J. Pawase, and KyungHi Chang. "Multi-UAV path planning utilizing the PGA algorithm for terrestrial IoT sensor network under ISAC framework." *Transactions on Emerging Telecommunications Technologies* 35, no. 1 (2024): e4916.
[28] Xu, Jinyong. "Efficient trajectory optimization and resource allocation in UAV 5G networks using

dueling-Deep-Q-Networks." *Wireless Networks* (2023): 1-11.

[29] Banafaa, Mohammed, Ömer Pepeoğlu, Ibraheem Shayea, Abdulraqeb Alhammadi, Zaid Shamsan, Muneef A. Razaz, Majid Alsagabi, and Sulaiman Al-Sowayan. "A Comprehensive Survey on 5G-and-Beyond Networks with UAVs: Applications, Emerging Technologies, Regulatory Aspects, Research Trends and Challenges." *IEEE Access* (2024).

[30] Khan, Naveed, Ayaz Ahmad, Abdul Wakeel, Zeeshan Kaleem, Bushra Rashid, and Waqas Khalid. "Efficient UAVs Deployment and Resource Allocation in UAV-Relay Assisted Public Safety Networks for Video Transmission." *IEEE Access* (2024).

[31] Lu, Yuxi, Wu Wen, Kostromitin Konstantin Igorevich, Peng Ren, Hongxia Zhang, Youxiang Duan, Hailong Zhu, and Peiying Zhang. "UAV Ad Hoc Network Routing Algorithms in Space–Air– Ground Integrated Networks: Challenges and Directions." *Drones* 7, no. 7 (2023): 448.

[32] Al Amin, Ahmed, Junho Hong, Van-Hai Bui, and Wencong Su. "Emerging 6G/B6G wireless communication for the power infrastructure in smart cities:Innovations,challenges,andfuture perspectives." *Algorithms* 16, no. 10 (2023): 474.