Intelligent Unmanned Air Vehicles for Public Safety Networks: Emerging Technologies and Research Directions

Zeeshan Kaleem, Ishtiaq Ahmad, and Trung Q. Duong

Abstract Unmanned air vehicles (UAVs) has shown great potential to enable numerous applications ranging from industry verticals to public safety communications. However, various challenges also arises with its integration into the existing terrestrial networks such as efficient UAV positioning, power allocation, trajectory design, and resource allocation. The existing conventional optimization solutions are not intelligent enough to overcome those challenges. Thus, real-time optimization and machine learning assisted solutions, and emerging technologies are required to overcome those challenges. To address those challenges, we summarized key technologies and research directions for UAV deployment at the edge or in the cell center, the power allocation and localization schemes, and the federated learning solutions.

Keywords Federated learning · RIS · Intelligent UAVs · UAVs localization · Machine learning

1 Machine Learning for Wireless Communications

The worldwide requirement for data traffic has endured around 1000×-fold increase over the previous years [1]. Due to the development of modern wireless communication networks, data traffic requirements are supposed to increase the capacity of future networks. In addition to a notable increase in data traffic, the latest communications applications, such as autonomous networks, wearable gadgets, Internet of

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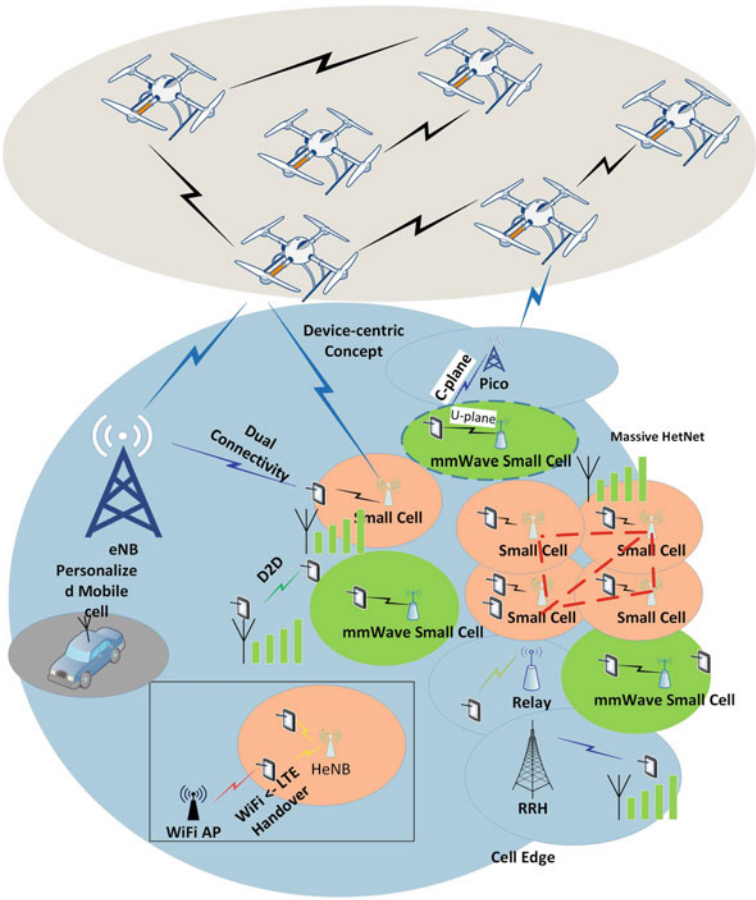


Fig. 1 Types of base stations to enable next-generation public safety networks

Things (IoT) devices, and cellular-connected unmanned air vehicles (UAVs) communications, continuously develop and produce immense data traffic with diverse requirements as shown in Fig. 1.

This development in communication applications demands an undeniable need for intelligent service, processing, and optimization of future communication systems. Using machine learning (ML), also known as artificial intelligence, into the design, planning, and optimization of future communication networks. The concept of ML has a lengthy and flourishing history. For instance, the use of neural networks (NN) for intelligent systems instead of utilizing a simple single-layer design to affect the state of one neuron. The idea of ML has established its powerful benefits in numerous fields, including robotics, computer vision, communications, and signal processing, where it is hard to find a detailed mathematical design for the characteristic pattern. In such areas, ML is considered a potential factor that does not demand any comprehensive model specification. The traditional methods that mainly depend on models and theories show weaknesses due to the extensive complexity of communication systems. Hence, research on ML for communication systems, particularly wireless communications, is currently encountering magnificent growth. For intelligent processing in a variety of scenarios, the emerging structure of ML acts as an enabler. The latest ML methods give a wide range of opportunities to develop intelligent communication systems that assists in addressing numerous challenges related to signal processing, classification, detection, channel estimation, resource allocation, routing protocols, configuring transport protocol, and user behavior interpretation. Various types of ML schemes have different usage in radio communication systems. It breaks the levels according to the kind of supervision demanded for training the ML models. Following are the three major categories of ML models.

1.1 Supervised Learning

Supervised learning model uses sample data with perceived results to estimate the output. Every sample data value is mapped to a single result value. The main purpose is to feed and train the model using sample data as input and with already known outcomes. After that, the already trained model predicts the results of the new input samples. Supervised learning is successful when there is a large amount of data to train the model. Hence, supervised learning is practical in deploying 6G to cope with rising traffic requirements. ML-based supervised learning collects performance computations such as throughput, outage probability, signal-to-interference and noise ratio, and pathloss for specific frequencies and bandwidth. ML-based supervised learning is used to predict the various performance matrix that a user will experience and adjust the different parameters accordingly [2]. ML-based supervised learning is adopted to train the models for pathloss prediction by considering channel state information (CSI) and approximate objective functions for associate propagation loss for 6G wireless systems.

1.2 Unsupervised Learning

An unlabeled collection of data is used to train the model with different characteristics and the system endeavors to identify subgroups with related features between the variables without having human involvement. Various schemes like generative deep neural network (DNN) and K-means clustering are advantageous when arranging devices for edge computing in a system. ML-based unsupervised learning is advantageous for uncertainty and detecting various faults in a system. It collects data in batches at data collection centers to decrease redundant data travel between distributed storage centers. It minimizes the latency by grouping nodes to automatically determine the node with low powers that must be promoted to nodes with more power for resource management in ultra-dense small cells.

1.3 Reinforcement Learning

Reinforcement Learning (RL) constantly works in probabilistic situations of wireless systems. In order to obtain excellent performance, the network parameters are modeled by using a Markov decision process (MDP) as shown in Fig. 2. RL continuously communicates with the environment, calculating the decisions at periodic intervals of time. The RL model needs to determine action at each point, obtained at the current state, to which the model provides a positive or a negative reward and updates the state. The rewards are associated with SINR and data rate. The RL is a data-driven approach that is not completely modeled from physics and mathematical-based modeling. Undoubtedly, wireless communication networks are human-made with lots of compositions that lack fast learning and transparency. Moreover, the state transition probability is free of all prior actions and states. While we require to optimize the system, the RL holds a record of all probabilities and their outcomes to obtain the absolute optimum decision. The principal grounds for RL to be applied to a radio communication system problem consist of (i) the signaling for obtaining the valuable data sets required to accurately operate the system is too complicated, (ii) the mathematical analysis of the wireless environment is considerably complicated to use in an agent and (iii) the desired results of RL is presented as a scalar reward. For example, the extensive machine-type communication and cell deployment (mainly small cells) where comprehensive system preparation is not achievable. We also summarized and compared key features of these three ML schemes in Table 1.

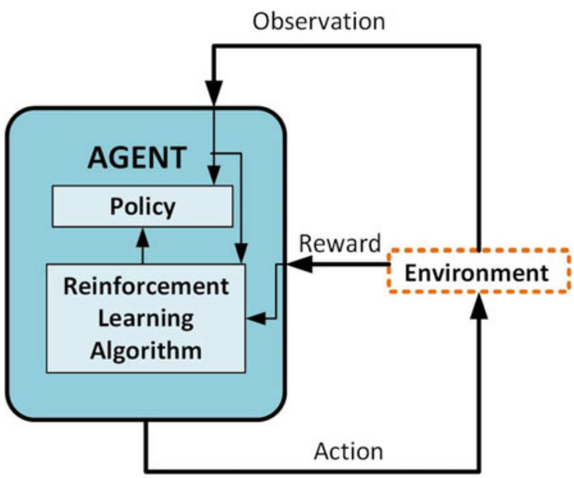
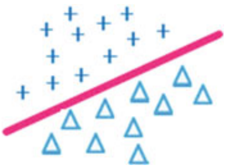
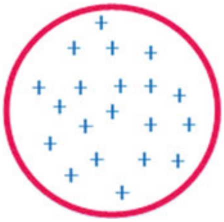
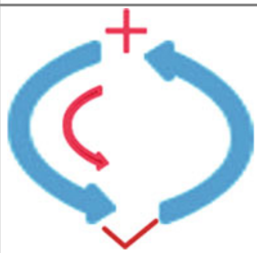


Fig. 2 Reinforcement learning working procedure

Table 1 Comparison of supervised, unsupervised and reinforcement learning

Supervised learning	Unsupervised learning	Reinforcement learning
		
Output is known	Output is not known	Interacts with the environment to make decision
Labelled data is used	Unlabelled data is used	Has no pre-defined data
Trained using past data	Trained using any data	Learning process rely on reward and policy
Algorithm is trained to predict output values	Algorithm is trained to discover similarities and differences in data	Algorithm learns by interacting with the environment using trial and error method
Highly supervised	Not supervised	Less supervised and rely on agent to find output
Learning predicts discrete value	Discover unknown patterns	Agent interacts with the environment to get rewards
Compute formula on the basis of inputs and outputs	Aim to find association among input and output value to sort them in groups	Aim to find the best possible reward by choosing suitable actions

2 Cellular-Connected UAVs for Emergency Communications

UAVs have applications in numerous fields ranging from civil to vertical industries as they can enhance coverage while supporting high mobility. UAVs also helps in enabling real-time sensing applications and emergency communications [3]. UAVs are getting popularity in provisioning emergency communications to the users in disaster-hit areas by serving as an aerial base station (ABS) [4]. UAVs can assist in carrying medical and food supplies to unreachable regions. With the assistance of ABS deployment, an emergency communication network is established to prevent further human lives and losses by connecting the victims with the emergency relief providing personals. Since, it is hard for a communication service provider to deploy a ground base station (BS) in a short time. Therefore, ABS are deployed to enable emergency communications or to increase the coverage of the functional BS as shown in Fig. 3.

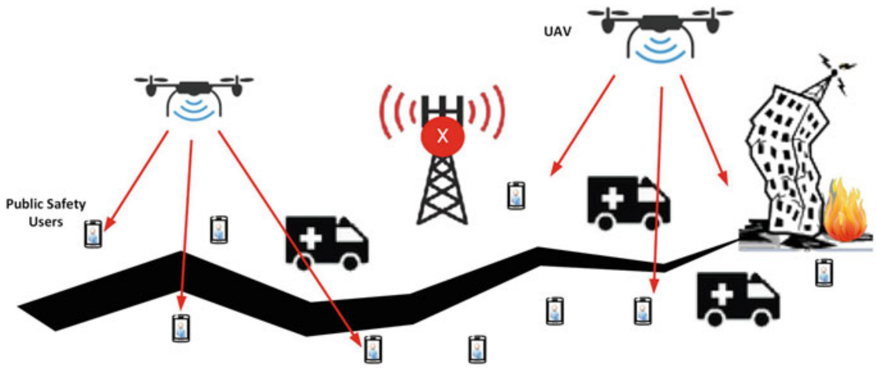


Fig. 3 UAVs-assisted public safety networks for coverage enhancement

Providing cellular connectivity to UAVs has enabled a plethora of applications ranging from online video streaming to enable emergency communications [5]. The Third Generation Partnership Project (3GPP), an industry-led consortium that standardises cellular networks, has been actively involved in identifying the key requirements, technologies, and protocols for aerial communications. To use enhanced Long Term Evolution (LTE) support for aerial vehicles, 3GPP successfully completed the first report in 2017 that led to 3GPP Release 15 Technical Report TR 36.777. That report highlighted the necessary requirements for UAVs to optimize their operations.

In 2019, 3GPP TR 22.829 identifies several UAV-enabled applications and use cases to improve and support 5G communications and networking technologies. During 2020 in Release 17, 3GPP mainly focused on two aspects: (1) infrastructure to support the connectivity and tracking in TR 23.754, and (2) application architecture to support UAV operations in TR 23.755 [6]. However, in order to provide UAVs with reliable wireless connectivity along with secure operation, a lot of challenges must be addressed, including interference management, mobility and handover management, and malware attacks prevention.

To enable these applications, multiple UAVs are required for zone monitoring during disaster situation. In addition, mutiple UAVs system can boost the system efficiency through joint effort. However, number of challenges exists in multiple UAVs system that includes localization, data processing at the edge, and trajectory planning and 3D ABS placement optimization [7, 8]. When compared to normal operating conditions, user association plays a significant role in emergency scenarios. In the case of a disaster, when the traditional terrestrial base station (TBS) is out of service, it becomes necessary to deploy UAVs in that area. Enabling device-to-device (D2D) communications [9, 10], in addition to UAV deployment, could help to improve coverage. The user association for numerous types of base stations is the key challenge in co-existing D2D and UAVs network. To address this issue, the authors in [11] explored how to solve the user association problem for UAV-enabled networks using D2D connections by maximizing the weighted sum rate of UAV users and total

Table 2 Related works in UAV communications

References	Brief summary	Placement schemes	Localization approaches	AI and distributed learning	Emerging technologies
[17]	Survey on object detection for low-altitude UAVs			√	
[7]	Comprehensive survey on UAV-assisted networks				√
[18]	Survey on communication and networking technologies for UAVs				√
[19]	Pervasive public safety communication technologies		√		
[20]	Important issues in UAV communications	√			
[21]	Survey on legacy and emerging technologies for public safety communications				√
[22]	Issues in cybersecurity, Privacy, and Public Safety			√	
[23]	Survey of public safety communications: User- and network-side solutions		√		
[24]	Survey on channel modeling for UAV communications				
[25]	Survey on collaborative smart internet of drones			√	
[26]	Survey on anti-drone systems: components,designs, and challenges	√			
[27]	Survey on applications, databases, and open computer vision research from drone videos and image				√
[28]	Survey on Collaborative UAV and wireless sensor network (WSN) for Monitoring		√		
[29]	A Survey on machine-learning techniques for UAV-based communications	√		√	
[30]	Survey on security and privacy issues for UAV communications			√	
[31]	Role of UAvs in public safety communications	√	√	√	√

D2D users. This difficult problem is tackled by presenting a learning-based clustering technique, which yielded sub-optimal results while being substantially simpler. As a consequence, this technique can be used to improve public safety wireless networks in the future.

In public safety communications, edge computing represents a paradigm change. Time taken to complete task is greatly minimize by placing edge computing centers in UAVs, which would minimize response time to consumers and save their lives. This strategy was described in [12], where the authors used user association, UAV trajectory, and user power to maximize offloaded bits from users to UAVs while considering the UAV's energy constraints and the users' QoS constraints. The trajectory of the UAV is significantly affected by various elements such as energy, flight time, and user needs.

UAVs equipped with Intelligent Reflecting Surface (IRS) are used in hazardous communication environments to provide public safety users with customizable services, quick deployment, low latency, coverage assurance, and a large amount of energy. UAVs-IRS defend mission-critical, high-priority public safety users from risks such as terrorism, natural disasters, and technological accidents. This communication helps to communicate and send the information (e.g., voice, data, and video) which improves the cooperation among of public safety users [13]. Due to malicious assaults or natural disasters [14], the BSs may be destroyed, leaving high-priority public safety users' without coverage. UAVs-IRS provide a direct or multi-hop by acting as a relay communication situation to address this issue [15]. When UAVs-IRS are used in conjunction with public safety networks, overall system congestion and communication coverage gaps are reduced. Adding flexible UAVs-IRS relays to disaster zones reduces the public safety users' outages dramatically. The coverage of public safety users' is significantly boosted after deploying UAVs-IRS relaying systems. UAVs-IRS can simultaneously give coverage to adjacent public safety users' and act as a relay to cover users that are positioned at a great distance by optimizing IRS reflection angle and phase shifts [16].

We summarize recent works related to UAV communications that covers various aspects such as ABS placement schemes, localization approaches, and artificial intelligence (AI)-assisted communications in Table 2.

3 ABS Placement, Power Allocation, and Localization for Emergency Communications

UAV-assisted communication infrastructure can provide high performance, capacity enhancements, and extended network coverage [32, 33]. They can explicitly provide mission-critical communications tasks with the facility of autonomous operations. Furthermore, UAVs play an important role in the distribution of critical information on the fringes of the fighting area as well as in the implementation of cellular networks. To provide the coverage extension, UAVs as a flying adhoc network (FANET)

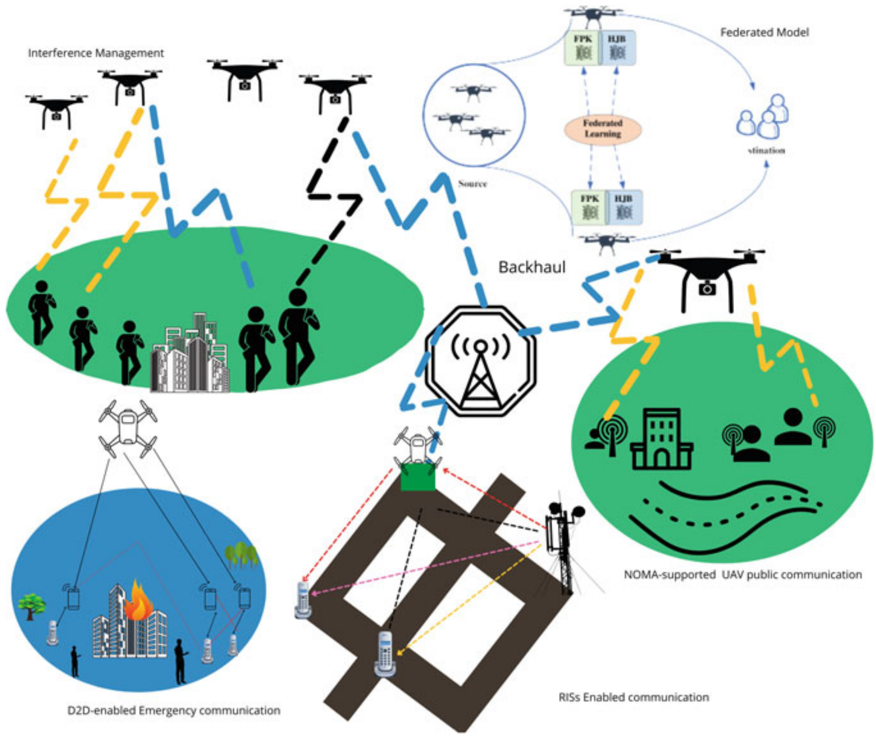


Fig. 4 UAVs-assisted public safety communication use cases

has gain the popularity [34]. We summarized some of the use cases to enable public-safety communications in Fig. 4.

A variety of future FANET communication architectures have been investigated including existing wireless technologies in the literature. However, selection of key communication technologies, architecture and core technology is truly a tedious problem to handle in FANET [35]. For instance, in [36] the authors presented a hybrid communication model, where they adopted features of 802.11 to meet high data rate requirements and 802.15.1 for low power consumption to enable FANET communications. This architecture considerably improved the network performance and reduced infrastructures costs.

In [37], the authors presented the advantage of coordination between UAVs and wireless sensor networks (WSNs). These two networks can support a wide range of applications, including search and rescue, navigation, control and recognition. The authors presented the solution for coverage enhancement using WSN-empowered UAV networks and argued that an efficient selection of way-points can solve several coverage issues.

To achieve high throughput gain during emergency situation, the authors in [38], presented the solution to optimally place the UAVs as an ABS in the disaster-hit areas. They achieved the improved average as well as an edge throughput. Similarly, the authors in [31] summarized the key contributions of ABS to enable public safety communications by targeting energy efficiency perspective. Moreover, they also proposed the ABS-assisted architecture that can assist the emergency users by enabling emergency communication services.

To enhance the users' coverage and improve their connection, the matching game algorithm is proposed in [39]. Moreover, they also propose a medium access control framework to optimize emergency efficiency and priorities emergency communications users. The simulation results proved the efficacy of the proposal within the affected areas. In [40], the authors presented a solution for different path loss models and deployment situations to enable ABS-assisted public safety communications in heterogeneous networks. By system-level simulations, the authors proved that they successfully improved the system performance by reducing the co-channel interference.

For ABS-aided relay system to enable emergency communications [41], the authors in [42] presented the joint optimisation of real-time ABS deployment and resource allocation scheme by proposing a fast K-means-based user clustering model. They also provided the centralized and distributed models to maximise the energy efficiency of the considered network under the tight QoS constraints. Numerical results verified the effectiveness of the proposed scheme.

To solve the challenge of path planning during disaster situation with limited battery and unknown user distribution constraints, the authors in [43] converted this challenge into multi-armed bandit problem. Then to efficiently solve this problem, they proposed two path planning algorithms which significantly enhanced performance in terms of number of served users.

The back-haul-aware optimization problem is presented in [44] to minimize the delay and search the ABS optimum altitude to maximize the users' coverage. They selected the optimum altitude by considering the minimum transmit power constraint. In [45], the authors jointly optimized the user association, resource allocation and 3D UAV placement to maximize the downlink sum-rate. They divided the problem into the three sub-problems and proposed the iterative solution that significantly enhanced the sum rate by reducing the co-channel interference. In [46], the authors targeted to maximize the network throughput by jointly optimizing the transmit power and UAV trajectory subject to the mobility constraints. They proved that the proposed scheme achieved notable throughput gains as compared to the conventional static relaying system.

In [47], to jointly optimize the ABS elevation and power control with the goal of reducing the concentrated outage probability, an iterative algorithm centered on the block coordinate descent (BCD) technique was proposed. Simulation results revealed that the outage probability was considerably reduced. In [48], the author proposed a framework that optimizes UAV trajectory and transmits power in order to improve the minimum throughput among UAV aided users. An iterative algorithm was proposed with the goal of reducing access delay and improving throughput.

Localization of the users is key during the disaster situation. To address this challenge, the authors in [49] presented a solution to transmit the discovery message over an ABS-to-user link. Simulation results proved that by using root-MUSIC algorithm the localization accuracy has been significantly improved. Similarly, in [50] data routing mechanism for localization in GPS-denied areas. The proposal focused on weighted centroid localization technique, where the position of unknown ABS are calculated using fuzzy logic. The proposed idea improves the localization efficiency by reducing the energy consumption and improving the lifetime.

4 Federated Learning for UAVs-enabled Public Safety Networks

UAVs as an ABS play key role in coverage improvement, capacity enhancement, and improving energy efficiency. During public safety communications, UAVs act as mobile terminal to enable applications like real-time video streaming for security personals. Here, UAV that act as an aggregator to globally train the model by collecting the locally trained model from the users, as shown in Fig. 5.

To efficiently implement this system, recently deep learning approaches has gained popularity to process the huge amount of received data. However, most of those processing are cloud centric, that in turn consumes huge power, consumes more bandwidth, introduce communication delay, and may pose security threats as it may contain UAV location and identity [51]. We compare the federated learning (FL) with the existing distributed and centralized learning schemes in terms of cost, accuracy, and latency in Table. 3.

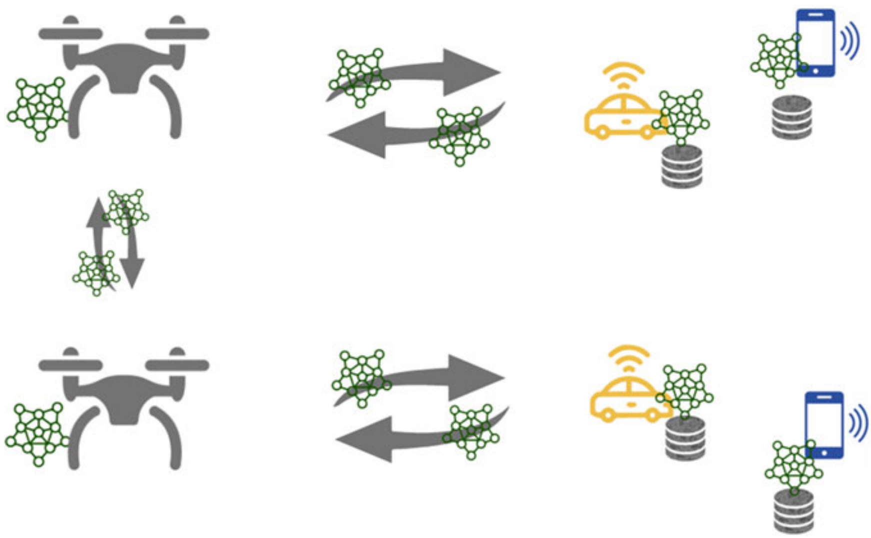


Fig. 5 Application of federated learning for UAV enabled public safety networks

Table 3 Comparison of FL with distributed and centralized learning

	Distributed learning	Centralized learning	Federated learning
Concept	Data is shared and process to multiple server parallel	Data collected at central server and process centralized manner	First client process their local data then local updates send to central server
Accuracy	Moderate	High	Low
Cost Feasibility	Cost effective	More costly	More cost effective due to locally sharing data
Latency	Less latency	More Latency than distributed learning	Latency is reduce to significant number from previous learning
Bandwidth	Less bandwidth require than centralized	More bandwidth needed	Updates are lighter so less bandwidth needed
Privacy	Privacy risk exist	Privacy risk exist	Due to exchange of Raw data privacy is not compromised

To overcome those challenges, recently Google introduced federated deep learning (FDL) or distributed deep learning concept [52] that has attracted huge popularity in communications, and specially in UAV communications during public safety, where only the locally trained models will be shared with the centralized entity for aggregation. This in turn significantly reduced the latency and power consumption as compared to centralized cloud processing as shown in Fig. 6 .

In FDL, deep neural network is collaboratively trained at the edge devices (UAVs in our case). Afterwards, the trained model is shared with the cloud to aggregate and create a global model. There are three main steps involved in this process; (1) training initialization, where as per requirements of the targeted application, hyper-parameters, initial global model, etc., are broadcasted to the UAVs by federated learning (FL) server, (2) each UAV collect new data and update parameters of local model based on the global model. Each UAV tries to optimize their parameters, and then shared those trained parameter with FL server, (3) after receiving those local parameters from UAVs, FL server aggregates them using the *FederatedAveraging* algorithm [53] and sends back the updated model parameters to UAVs. At FL server, the received parameters are optimized by minimizing the global loss function. More details about those steps are summarized in [51].

In public safety communications, UAVs have to execute various tasks that ranges from trajectory planning to target recognition. To address this challenge, the authors in [54] presented framework to implement FL algorithms for UAV swarms. In UAV swarm, one UAV as a leader gather the locally trained data from each of the following UAV, generate global FL model, and then transmit it among the followers UAVs. In order to optimize the the convergence rate of FL, joint power allocation and

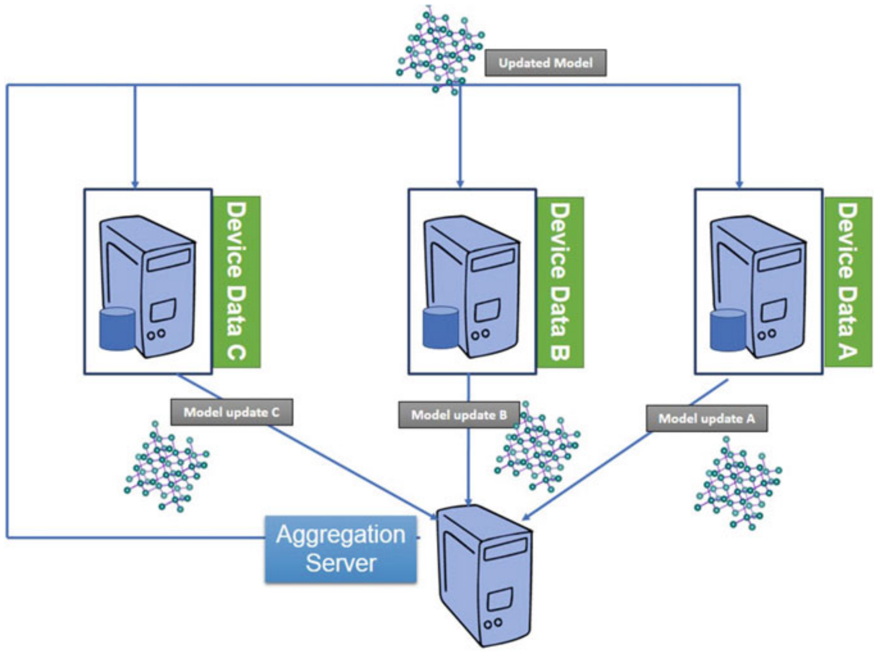


Fig. 6 Federated learning procedure for privacy preserving in safety networks

scheduling scheme was proposed by taking care of energy and delay constraints. Simulation results proved the effectiveness of the proposal by significantly reducing the communication rounds as compared to the baseline schemes.

Mobile crowd-sensing is key for successful implementation of emergency communications as it assists in indoor positioning and environment monitoring. Moreover, the combination of UAVs with AI has open ways for efficient mobile crowd-sensing [55]. However, the conventional existing AI models may arise serious security and privacy threats. To overcome this threat, FL proved a promising solution because of opening the possibilities of collaborative learning and training of the model without exposing the sense data. To improve this security further, the in this paper the authors introduced blockchain-based learning architecture that improves the privacy of local models. Results proved that the security was improved by introducing effective solution of model sharing as compared to the baseline schemes.

In [56], to reduce the processing load in multi-UAV networks the authors proposed an asynchronous federated learning (AFL) framework to enable asynchronous distributed computing that disallows transmitting the raw data to UAV servers and trained them locally. Moreover, to further improve the efficiency and maintain quality of service the device selection strategy was also introduced. The authors improved the convergence speed and accuracy considering asynchronous advantage actor-critic for joint device selection, UAVs placement, and resource management scheme [57].

In disaster hit areas, the thorough inspection of local updates at UAVs is necessary to guarantee privacy. To overcome this challenge, the authors in [58] combined blockchain with FL and replaced the centralized FL platform with a UAV-assisted FL with blockchain at edge. Results verified that the proposed framework was suitable to enable intelligent disaster communications that consumes less energy.

5 Conclusion

In this chapter, we have summarized the key technologies related to intelligent UAVs to enable public safety communications and also discuss future research directions for researchers. We have concluded that the intelligence plays key role in improving the UAVs performance in terms of coverage, throughput, mobility management, and computation at the edge to enable public-safety communications.

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