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Channel tracking in IRS-based UAV communication systems using federated learning

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This paper aims to overcome the problems and limitations of the communications of Unmanned Aerial Vehicles (UAV) by incorporating Intelligent Reflecting Surface (IRS) into UAV for channel tracking. Since IRS may change the propagation environment, is a desirable option for combining with UAV to improve wireless network security. Due to its capacity to proactively configure the wireless environment, IRS technology is a potential one for future communication systems. IRS is able to provide steady communications and serve a greater coverage area by reflecting signals to create virtual LoS routes. Moreover, we develop a federated learning-based channel tracking technique in which federated learning is used to determine the security and pre-estimation constituent. In addition, for channel tracking, Long Short-Term Memory (LSTM) is developed. Due to their ability to understand long-term connections between data time steps, LSTMs are frequently used to learn, analyze, and classify sequential data.

Keywords: channel tracking, FL, IRS, LSTM, UAV

1 Introduction

Unmanned aerial vehicles, or UAVs, are also referred to as drones. UAV is a plane without a human pilot, flight crew, or passengers. Unmanned Aerial Systems (UAS) involve a surface operator and a communications network along the UAV, including remotely piloted aircraft. UAVs have emerged as a feasible candidate prototype for supplying communication and processing capabilities for terrestrial mobile devices in recreation complicated systems, outdoor events, significant heat flux, and remote places. UAVs were created in the modern era for military duty in areas that were "dull, unclean, or hazardous" for people, and by the twenty-first century, drones had become essential resources for the majority of forces. As control technology advanced and prices decreased, they could be used in an array of non-military applications. Monitoring of forest wild-fires, use of drones, systems and delivery, agriculture, law enforcement among security, infrastructure inspections, and other activities are some of them.

UAV-based networks have been effectively employed for rapid wireless technology, data collecting, machine learning (ML) instruction, and network augmentation thanks to their mobility, agility, flexibility, and good line-of-sight (LOS) propagation [1]. UAV-assisted computing and communication tasks have recently attracted a lot of attention in 5G and other wireless networks. Again, using UAVs as flying BSs provides additional flexibility in data collection and ML modelling training for lowland devices, but due to security issues and limited data transfer resources, it is impractical for a wide range of phones to upload their original information to UAV servers. Furthermore, processing and training huge amounts of data remain difficult due to UAVs' low power density, storage spaces, and computing capabilities [2]. Cellular connections [3, 4] and other academic fields are growing to be interested in ML approaches. The massive amount of produced traffic data and the inefficiency of conventional model-based solutions, which cannot handle the increasing complexity and heterogeneity of the forthcoming generations of wireless networks, are what drive the use of techniques based on machine learning in wireless networks. Cordless devices can learn and estimate the dynamic behavior of various networking features, such as patterns of traffic, network-based interactions, data context, content inquiries, and so on. This allows them to intelligently control their environment and take more proactive actions. Additionally, DL, the foundation of ML, is evolving into one of the most popular data mining components, surpassing conventional ML techniques. Contrarily, traditional machine learning methods rely on the cloud and need for data to be sent to and analyzed by a central location like a data center or cloud platform. For UAV-based

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wireless, these machine-learning approaches are inappropriate [5-7]. Beginning with the fact that the information gathered may contain private information like the whereabouts and identification of UAVs, private data may not be accessible. Second, given the limited capacity utilization and the continuous stream of unprocessed data kinds, such as multimedia material types, that drones continuously transmit to the cloud, the network must have high bandwidth. Last but not least, cloud-centric approaches have unacceptable latency, especially for applications that demand real-time decisions, including autonomous drone surveillance and UAV-based virtual reality applications.

Decentralized learning systems are therefore essential for processing scattered sub-datasets produced by UAV devices in an effective manner. The FL concept (federated learning) was introduced by Google. By letting devices develop machine learning algorithms locally rather than transferring initial information to a server, FL seems to be a potential way for maintaining device confidentiality, *ie* by maintain privacy we can secure data [8, 9]. Federated learning is a method for deep learning that includes training an algorithm over several distributed networks of edge or servers that maintain local data samples while transmitting them in a synchronous or asynchronous way. In a synchronous federation, it spends the majority of its time idle because it has to wait for every selected device to complete its local training. In an asynchronous federation, it does not wait for every model to transmit and transmits to the global model for aggregation [1]. Federated learning is also frequently referred to as sharing knowledge [10, 11]. Federated learning makes it possible for many clients to create a robust artificial intelligence method without sharing information, allowing for the resolution of critical issues such as confidentiality, security, data access obligations, and openness to heterogeneous data and provides a good bandwidth, communication overheads that led to efficient usage of energy with different neural networks [2, 3]. It needs local models for the transmission of the data which then globally aggregates, and not efficient by having only the global model [4]. It is employed in a variety of fields, including the military, communications, IoT, and pharmaceutical research. In order to create an optimization strategy that is maintained by all nodes, the fundamental concept is to develop localized modelling on localized sample data and regularly share data (for example, including the weights of connections of the deep learning model) between local nodes.

Although UAV-aided solutions are thought to be promising technologies for wireless communications in the future, the complicated urban environment may cause LoS links between ground users and navigation UAVs to become blocked. With various technologies, such as crop classification the techniques such as machine learning, and deep learning are used for drones nowadays [5]. An essential tool for combating signal path loss and protecting communications is the ability of IRSs to build virtual LoS routes to improve the reliability and reach of handheld propagation, this helps in making good frequency. This is so that signal strength can be directed in specific areas and information leakage can be reduced by the low-cost IRS's ability to intelligently adapt phase shifts [6]. An IRS is used as a relay in the proposed IRS-assisted UAV SWIPT system in order to enhance system performance [7]. Therefore, IRSs can be implemented to let the UAV provide ubiquitous communication services in order to tackle the blockage issue affecting UAV-aided systems and to adjust phase shifts effectively [8]. Installing IRSs that are within a UAV-aided system can help address the time- and energy-intensive problem caused by UAV direction when some users are far away. It demonstrated how quickly and reliably UAVs and terrestrial base stations can establish and maintain a communication connection and one-step semidefinite development-based artificial intelligence method [9, 10]. Deploying both UAV and IRS in a wireless network can hence significantly improve communication performance due to their alluring advantages. Furthermore, it is essential to obtain precise information about channel states (CSI) for efficient transmissions in order to achieve exceptional communications.

Figure 1 illustrates the wireless link of the IRS-UAV with the k^{th} number of users. Although LoS linkages can be established and communication distances reduced using UAVs to provide a stable communication environment, there will always be occasional obstructions to communication channels caused by things like trees and big buildings. IRS-assisted UAV communication is a novel approach that is receiving more and more attention. As an illustration, researchers looked into the fair concealment energy conservation in a structure where a movable UAV relay had been fitted with an IRS and jointly built the UAV flight and IRS forming beams to optimize the system's maximum achievable rate. IRS also demonstrate the covert communication technique with UAV-IRS assistance, which raises the rate of covert transmission [11]. A study is being done on the IRS-assisted UAV transmitting system, which uses the IRS on the building to help with the interaction between the equipment and the UAV. Similarly, to that, think of the mechanism that enables an IRS and a UAV relay.

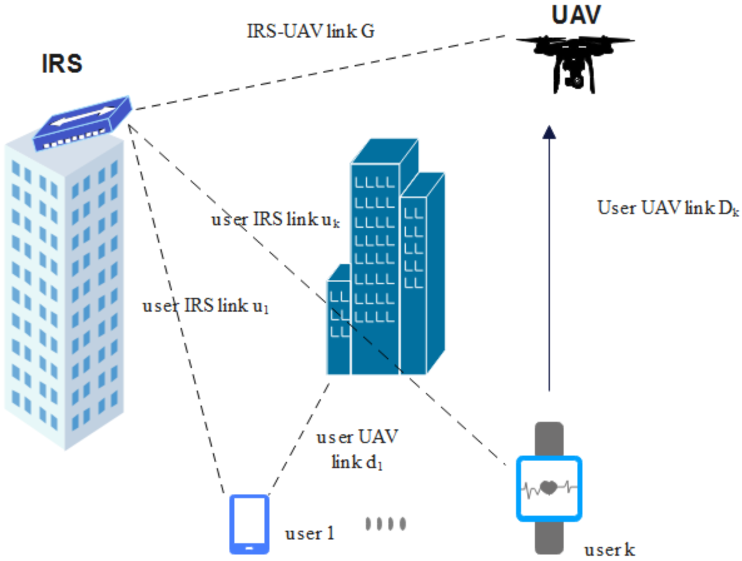

Fig. 1. IRS-based UAV multiple-user communication system

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2 Motivation and contribution

In contrast to earlier artificial intelligence tools [12], federated learning trains and optimizes a deep learning model by facilitating communications between distributed local customers and central servers [13, 14]. Although LoS linkages can be established and communication distances reduced using UAVs to provide a stable communication environment, communication channels will inevitably periodically be obstructed by objects like trees and tall structures [16, 17]. Attention to the novel method known as IRS-assisted UAV transmission has grown. For instance, the UAV path and IRS beamforming could be collaboratively designed to maximize the system's average attainable rate. The IRS-assisted drone relaying system, which employs the IRS on the structure to aid in communication between the device and the UAV, is the subject of research. Then, by reducing the decoding error rate, the IRS passive beamforming and UAV location were simultaneously optimized. In order to ensure the success of IRS-assisted UAV communications systems, a trustworthy channel tracking method must be developed. The three main issues to be solved are good estimating efficiency, low pilot costs, and the time-varying channel caused by the mobility of both drones and users who are mobile. As a result of the previously mentioned literature review, we propose an FL-based channel monitoring approach for IRS-assisted UAV-enabled communication systems with lower learning overheads and notably improved tracking performance. The following is a summary of the major contributions:

- For the centralized IRS, navigational UAV, and handheld devices in the IRS-assisted UAVs-enabled communications system, it generates a 3D geometry-based variable channel model. We create the time-variant channels model by coupling a dynamic transmitted virtual LoS connection (user-IRSUAV) to an activation variable and a dynamic LoS link (user-UAV) and a blockage parameter. The spread delays, maximum Doppler effects, velocities, and temporal delays are all precisely included in the system model.
- To track the time-dependent channel in the created system, we provide an FL-based multichannel tracking technique. Channel pre-estimation and carrier tracking are the two modules that make up the suggested method. A network of Deep Neural

Networks (DNN) is used to execute offline training on a pre-gathered training dataset in order to achieve the pre-estimation. FL with DNN is used to secure the channel tracking procedure. Also, FL improves the network bandwidth and efficiency. In order to track a CSI over a time-varying route in a data-driven manner, the tracking module is built as a stacked bi-directional short brief-term memory (Stacked Bi-LSTM). The Stacked Bi-LSTM is built using a framework that includes a bidirectional structure over numerous stacked layers and a specific historical trace-back time frame in the time sequence.

- The proposed channels tracking technique needs fewer convergence epochs for the loss of function during the unplugged training stage than the benchmark algorithms. Additionally, simulations reveal that the suggested technique (DNN followed by Stack Bi-LSTM) has comparable complexity and exhibits superior channel tracking efficiency with fewer pilot expenses than the benchmark algorithms.

3 Related works

For multi-UAV networks, Yang created an asynchronously united teaching model [1] that can provide asynchronous computing services by enabling model training locally without sending raw, sensitive data to UAV servers, enabling asynchronous distributed computing. Additionally, it has a device selection system that makes sure that low-quality equipment does not reduce training effectiveness and precision. In order to improve the speed and accuracy of federation converging, the author also offers an A3C-based combined component selection, drone deployment, and resource management technique. Simulated findings show that the suggested architecture and method achieve more precision and faster federation execution time when compared to prior approaches.

Yang demonstrated federated learning-based energy-efficient UAVs in [2]. This article examines the problem of resource allocation for FL across UAVs and efficient energy transmission. With the intention of lowering the device's overall energy consumption while keeping a time restriction in mind, both the local computation and transmission energy challenges are approached as optimization problems. The author generates the time needed for the delivery minimization problem and suggests a bisection-based approach to obtain the best answer, which would be a workable solution to the first energy minimization problem because the iterative technique the author suggests is required a realistic option.

An RF frequency-based UAV recognition method was put forth by Al-Emadi [3]. The author presented a CNN and DNN comparison as well as an RF signal-based approach to drone identification and classification. The author used a deep learning technique known as CNN to build an effective drone detection mechanism for this system. The proposed model was evaluated and trained using a dataset. To investigate and assess the performance of this model, the author analyses data obtained using ANN, CFAR, or H.O.C. CNN has an extensive variety of uses due to its special characteristics that combine extraction of features into one model, particularly in recognizing and categorizing problems. In this work, the author stresses dependability and exceptional performance. According to the author of this study, drone detection and recognition are more precise and provide superior performance. In order to shorten UAV flight times while retaining reliable internet connectivity, Khamidehi developed a federated-based architecture [4], because UAVs are unable to develop the global model independently. As a result, the writer provided the following two options: 1) Using FL, the UAVs cooperate to build a large model of the possibility of an outage in the environment. 2) Based on the representation created in the first phase using fast random trees (RRTs), the author provided a path-planning technique.

In [5], Bouguettaya focused on CNN-based crop/plant classification methods applied to aviation spatial data processing in order to let researchers and manufacturers choose which strategies to employ according to the crops and hardware they have been researching. This paper's author addressed different crop categorization methods using deep learning. UAVs' advantages over conventional technologies were praised. The study also investigated a number of equipment and pixel-based techniques to assist farmers and analysts in selecting the appropriate organizer based on the goal crop, camera sensors employed, and other framework aspects.

An IRS is used as a passive relaying system on a UAV in this letter by Song [6], with the UAV acting as a versatile flying platform. The communication schedule, IRS phase shift, and UAV trajectory are all collaboratively optimized in order to maximize the minimal average transmission rate. This problem is challenging to directly solve due to the coupling of the optimization variables and non-convexity. As a result, the author splits the issue into three smaller issues and uses the sequential convex approximation (SCA) method to iteratively resolve each issue. By using the suggested iterative technique, the bare-bones rates of transmission can be significantly increased, and the algorithm's usefulness is also supported by numerical findings.

The simultaneous wireless knowledge and authority transfer (SWIPT) network that is enabled by UAVs is given an IRS in this research by Wang [7]. In the proposed IRS-helped UAV SWIPT system, an IRS is deployed as a relay to improve system performance. A multi-antenna UAV functions as a line for transmission examination device that communicates with single-antenna data decoding recipients (IDRs) while guaranteeing the power needs for energy harvesting receivers (EHRs). Under the restrictions of the UAV's transmit power and the energy conservation requirements of EHRs, we jointly optimize the hover position, the UAV's beamforming vector, and the phase shift at IRS in order to maximize the minimal throughput of IDRs. The formulated issue is non-convex and variables are highly coupled, so an effective algorithm is required. The suggested IRS-assisted UAV SWIPT system, when compared to UAVs-aided SWIPT or IRS-assisted SWIPT system, considerably enhances performance gain when it comes to minimum bandwidth maximization, according to numerical results.

This paper examines a straightforward design for multi-input single-output no orthogonal multiple access (NOMA) downstream networks supported by UAVs by Singh [8]. The objective of this study is to increase the rate of strong users while maintaining the target rate of weak users as determined by the optimal UAV horizontal position beginning by strategically placing the IRS-UAV. After that, we suggest an iterative approach to alternately optimize the transmit beam forming with a phase shift of IRS. The optimal beamforming vectors' closed-form expressions are developed for beamforming optimization. Then, based on the results of the beamforming, we suggest two techniques for obtaining IRS's ideal phase shifting. One is an iteration approach based on a semidefinite relaxation that offers a high data rate, while the other is based on a sequential convex approximation technique that has a low level of complexity. Finally, simulation results are shown to demonstrate that the performance of the two suggested algorithms is noticeably superior to that of the IRS-based UAV-assisted symmetrical frequency-division multiple access technique and the random phase shifting scenario. Table 1 presents the comparison of existing DL/FL/IRS-based UAVs.

Feng [9] presented that fast establishment and maintenance of the communications connection between UAV and terrestrial base stations is difficult. An IRS-aided rapid connectivity UAV adaptive beam realignment (IRS-UAV-ABA) method using a double-layer short- and long-term memory (DL-LSTM) geographical angle forecasting approach is suggested as a solution to this problem in order to increase the efficiency and dependability of the UAV interaction. First, a model for DL-LSTM enabled spatial perspective prediction is created to make it easier to determine how much of the beam should follow the UAV's real-time flight trajectory. Second, the IRS phase shift matrix and the BS beamforming vector are suboptimally solved using the non-convex optimization approach for maximizing the received information to noise ratio of moving UAV. Finally, the proposed IRS-UAV-ABA method can perform adaptive dual-beams synchro-nization from BS to UAV and additionally from IRS to UAV using the aforementioned beaming vectors, phase shift matrix, and adaptive beam coverage. Simulation findings show that the proposed approach not only has improved spectrum efficiency and consistent beam-forming gain, but also effectively prevents the beam misalignment brought on by the mobility and disturbance of UAVs.

Wang [10] proposed an IRS- and UAV-guided two-way amplify-and-forward (AF) communicate wireless system where User1 (U1) and User2 (U2) can communicate each other because of a UAV-mounted IRS and an AF relay in order to improve the message exchange rate between them. The AF relay beam formation matrix and the IRS phase change of two time slots are the variables that need to be adjusted in a problem of maximization of minimum rate. The expression of the AF relay beamforming array can be derived in a semi-closed form by the ZF method, and IRS transition vectors of two time slots can be optimally optimized by using the SCA algorithm. This low-complexity alternately incremental (AI) scheme is based on zero forcing along with successive convex approximation (LC-ZF-SCA). A high-performance AI approach based on one step semidefinite development and sanctions SCA (ONS-SDP-PSCA) has been offered to achieve a noticeable rate enhancement. The beamforming matrix at the AF relay can be solved first using a single-value decomposition and the ONS method, and IRS phase shift frameworks of two time slots are refined by SDP and PSCA computer programs.

Wang [11], 2023 proposed the UAV-IRS assisted covert communication method that increases the covert transmission rate. In particular, Alice, the ground transmitter, surreptitiously transmits the confidential message through a legitimate recipient, Bob, via the UAV-IRS, hoping that the warden, Willie, won't be able to catch it. Willie is also hostile toward Alice and with UAV-IRS, making it challenging to pinpoint his precise location. By this information, the authors in [11] first choose the best detection threshold and calculate the likelihood that an error would be detected at Willie, which represents the worst-case scenario for the valid transmission. Then, in accordance with the covert requirements, the authors in [11], optimize Alice's transmit power, the IRS phase shift, and the UAV-IRS's horizontal location in order to maximize the covert rate of transmission. In order to show the viability of the suggested covert communication strategy supported by UAV-IRS, numerical data are presented.

In the present study, we have created the network where UAV is being with IRS in a communication system, 3D geometry dynamic channel model. The movement of mobile device owners and UAV navigation are taken into account when building the time-variant channel. The dynamic LoS connection (user-UAV) and dynamic simulated LoS link (user-IRSUAV) are the two main dominant linkages in the channel model. Also, the stacked Bi-LSTM is used. A bidirectional design has been devised to overcome the limitation of a single LSTM cell, which can only collect historical data, and allow for the utilization of both past and subsequent data. The Stacked Bi-LSTM system specifically uses a bidirectional framework spanning numerous stacked layers to track historical data over time.

Table 1. Summarized comparison of existing DL/FL/IRS-based UAV computing frameworks

Ref. Year	UAV	DL/FL /IRS	Focused area	Key issues	Key technologies	Remarks
2020 [1]	✓	FL	Asynchronous federated learning	Federated execution time is slower and accuracy is low.	Proposed A3C algorithm to address the problem.	Asynchronous with the device provides more accuracy.
2020 [2]	×	FL	Energy consumption of wireless networks	Energy consumption is high.	An iterative algorithm is proposed where a solution for bandwidth and learning is derived.	Energy consumption may be minimized.
2019 [3]	✓	DL	Detection of drones using CNN.	The significantly slower operation, a higher computational cost.	Proposed a solution using a different neural network that reduces the cost and improves operation.	CNN with more recognition and classification.
2020 [4]	✓	FL	Minimization of travel time of UAVs ensuring reliable internet connectivity	UAVs cannot rely on their own to build the global model	Developed path planning algorithm	The algorithm satisfies the cellular connectivity requirements
2022 [5]	✓	DL	Focused on CNN-based crop/plant classification methods used for UAV-based remote sensing picture	Doesn't process precision accurately	Proposed CNN for image processing techniques	Deep learning approaches emerged as a powerful tool to classify the different crop types accurately.
2022 [6]	✓	IRS	Enhancement of maximization of the transmission rate	Jointly optimizing the communication schedule, phase shift, and trajectory in IRS	Proposed SCA and relaxation techniques. also, TDMA technology assists the multi-user communication	Effectively enhance the minimum average transmission rate
2021 [7]	✓	IRS	Focused on improving gain in terms of minimum throughput	Throughput maximization problem	Proposed IRS-assisted UAV SWIPT system	The proposed algorithm improves performance gain
2023 [9]	×	IRS	To expand the access point's communication range	To improve SNR in the particular targeted area	Proposed algorithm by the passive beamforming of the IRS's location and then deploying the IRS	Achieves better coverage performance.

4 Terms related to proposed methodology

Federated learning: Federated learning addresses important challenges including confidentiality of data, data security, data right of access, and access to diverse information by allowing different players to develop a single, strong artificial intelligence model without sharing data [15, 18].

DNN: A neural network with a specific degree of complexity is known as a DNN, additionally referred to as Deep Nets. It can be compared to stacked neural networks, which are neural networks with several layers, typically two or more, and at minimum a single undetected layer in between [16, 17].

RNN: One of the two major categories of artificial neural networks, recurrent neural networks are distinguished by the direction of information flow between their layers. A kind of recurrent neural network called the short-term, long-lasting network was developed to address the vanishing gradient issue that plagues conventional RNNs. Its benefit over alternative RNNs, hidden Markov models, and other sequence techniques for learning is its relative inability to gap length [16].

BiLSTM: A neural network with recurrent neurons used largely for natural language processing is called Bidirectional LSTM (BiLSTM). Unlike traditional LSTM, it may use data from both sides and has input that goes in both directions [10].

Stacked Bi-LSTM: A Deep Neural Network that incorporates both LSTM and BLSTM is known as a Stacked bidirectional and the unidirectional the LSTM algorithm (SBU-LSTM) Neural Network. known as SBU-LSTM. An SBU-LSTM Training System (which employs an SBU-LSTM Training Algorithm) can train it. Typically, it can be used to forecast the speed of network traffic [18].

5 Proposed methodology: Channel tracking in IRS-UAV

Channel estimation is increasingly frequently created and used with data-driven FL-based frameworks. Furthermore, FL-based algorithms are computationally simple and can perform basic operations like multiplications. All of those FL-based channel estimation projects, however, disregard the CSI's temporal order. To put it another way, closer observations of the dynamic CSI can be used to make more accurate predictions. Giving neural networks the capacity to learn the behaviour of relationships across time domains is important to follow the time-varying channel. Recurrent Neural Networks (RNN) and LSTM are two extensively used techniques for tackling time-varying problems, including natural language processing.

5.1 System model

In order to predict, both approaches take into account the information from both the past and the present data. RNNs in particular have feedback loops to preserve information over time. The vanishing gradient problem makes it challenging for RNNs to learn long-term temporal dependencies. To preserve long-term dependence on handling gradient flow better, LSTM incorporates input and forget gates. This section proposes a Deep Neural Network (DNN) for monitoring that is being followed or supported by a Stacked Bi-LSTM structure. This framework combines the benefits of different inputs having LSTM and output layers on passing data with time domains along with DNN with a multiple-layer perception mechanism for obtaining traits of complex environments. The proposed algorithm's general structure is depicted in illustration form. Framework for DNN Channel Estimation with additional layers that are concealed between the input layer and output layers, DNN is an expansion of neural network technology. To be more precise, every layer that is hidden has numerous neurons, and every result is the weighted average of those neurons, which is run through a nonlinear function, both the Sigmoid and ReLU functions. In Fig. 2, the pre-estimation DNN is displayed with hidden layers among the total L layers. Figure 2 is illustrated in three steps: Fig. 2(a), Fig. 2(b), and Fig. 2(c) that describe the input, the training for pre-estimation using DNN model and output, respectively. Neurons make up the network's hidden layer. $X_K(t)$ is the DNN input vector that is received from the UAV from K^{th} user and $Y_K(t)$ is the output vector and channel matrix that needs to be estimated. The pre-estimation implies $Y_K(t-T)$ to $Y_K(t)$.

5.2 Architecture and working

Stacked Bi-LSTM traces the various time sequence as another module of the all-inclusive algorithm architecture using pre-estimation denoised channels information and previous channel monitoring output. Figure 3 illustrates the stacked Bi-LSTM channel monitoring. The channel monitoring of stacked Bi-LSTM proposes $Y_K(t-T-1)$ to $Y_K(t-1)$. Thus, it is the progressive consequence from $t-T$ to $t-1$. The preceding time slot that was utilized by the model is represented by letter T. Additionally, the reversible time continuity from $t-1$ to $t-T$ is used to determine the output of the reverse stage.

1) **LSTM:** The LSTM represents a gradient-based algorithm for learning that serves as an improvement to recurrent neural networks by making connections between prior knowledge and the current task. The moment sequence data is often sent forward along the chain-like architecture to the LSTMs.

2) **Stacked Bi-LSTM:** It is shown that in order to get over the constraint of a single LSTM cell, that can only collect history data, a bidirectional configuration has been developed that includes in both directions alignments to be able to use historic and subsequent data. Specifically, the stacked Bi-LSTM system tracks historical data over time using a bidirectional framework spanning several stacked layers. The layered Bi-LSTM channel monitoring suggests $Y_K(t–T–1)$ to $Y_K(t–1)$. So, from $t–T$ to $t–1$, it is the forward outcome. Letter T stands for the previous time slot that was used in the model. The output of the backward stage is also determined using the reversible time continuous from $t–1$ to $t–T$.

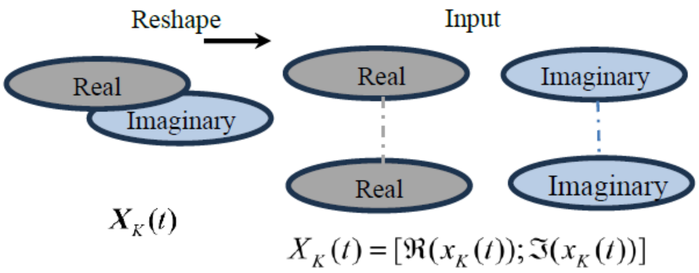

Fig. 2(a). Input stage DNN channel pre-estimation model

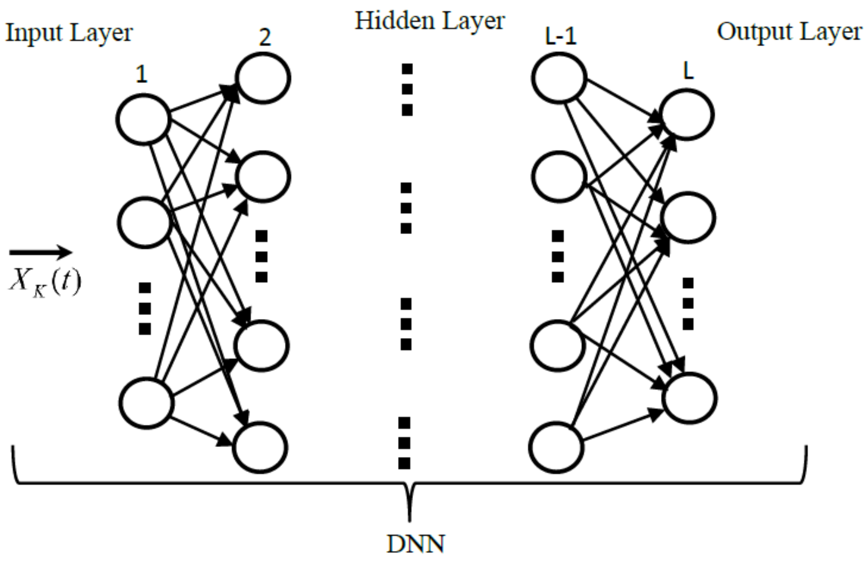

Fig. 2(b). DNN channel pre-estimation

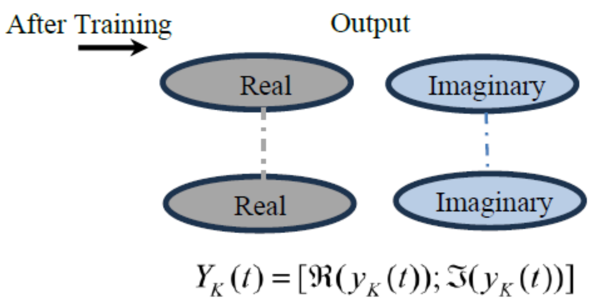

Fig. 2(c). Output stage of channel pre-estimation model

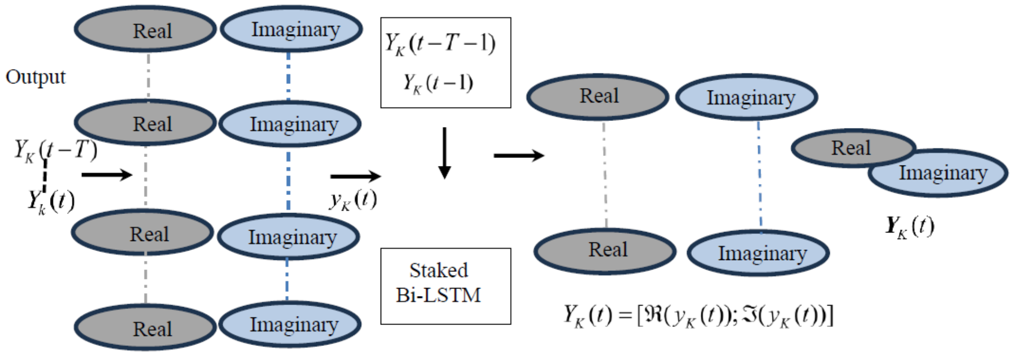

Fig. 3. Channel tracking algorithm

While the IRS-assisted UAV system appears to be an affordable solution to support smart cities, including smart factories, smart buildings, and smart hospitals, research on this exciting combination of these innovations is still in its early stages. An IRS often requires a static and restricted energy source, which is largely disregarded, because it lacks a power amplifier. However, low battery endurance and significant energy consumption make UAV energy conservation crucial since they often represent a major barrier restricting UAV performance and battery endurance.

6 Experimentation, results and discussion

This section evaluates the channel monitoring achievement as well as the loss of training in various methods. We specifically examine the channel tracking effectiveness of DNN, also DNN accompanied by LSTM, Bi-LSTM, and Stacked Bi-LSTM based on a structure with two modules. We mainly concentrated on evaluating the suggested algorithm for DNN next followed by Stacked Bi-LSTM. Table 2 depicts the basic parameters used.

Table 2. Basic parameters

Parameters	Value
Carrier frequency	5.2 GHz
UAV speed	5 m/s
Azimuth angle	π/6
Elevation angle	π/6
Antenna angle	π/6
Flat angle	π/6
IRS reflection elements	8
Height of IRS	100 m
No. of antenna elements	8
Height of UAV	200 m

6.1 Simulation setup and parameters

We have categorized the performance of our suggested channel tracking algorithm in this part according to various specifications or values of parameters. For the channel tracking performance, there are other parameters like the normalized mean square error having small pilot overheads, complexity, carrier frequency 5.2 GHz, speed of 5 m/s, height of UAV 200 m, antenna elements are 8, number of IRS reflecting elements are also 8 are used.

6.2 Results and analysis

Figure 4 illustrates the loss value for the channel's pre-estimation DNN with various pilot overhead sizes P and hidden layers L.

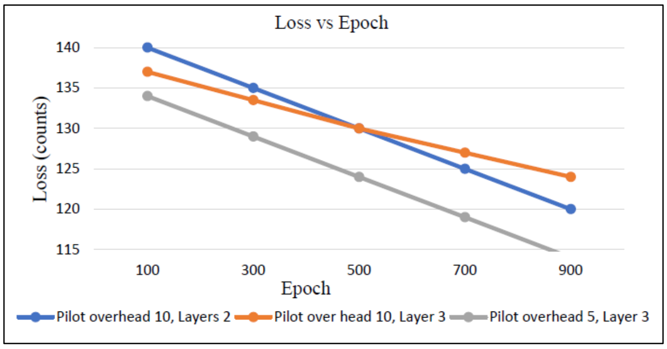

Fig. 4. Channel pre-estimation of different number of pilot overheads and DNN layers

The learning rate is set at 0.001, with 200 repetitions used to pick the entire training data set. It can be seen that longer epochs are needed to bring the loss function into convergence when L=3 in addition to P=5 and 10. Between L=3 there is no discernible variation in the loss function's tendency to converge. Additionally, P=5 pilot overheads have a lower con-vergence than P=10. The cause is because when P rises, each layer's input size and number of neurons both rise, giving rise to a more complicated structure. According to empirical data, our model can generate a significant performance boost with a relatively low *P*. *P*=5 and *L*=3 are therefore chosen for the remaining runs.

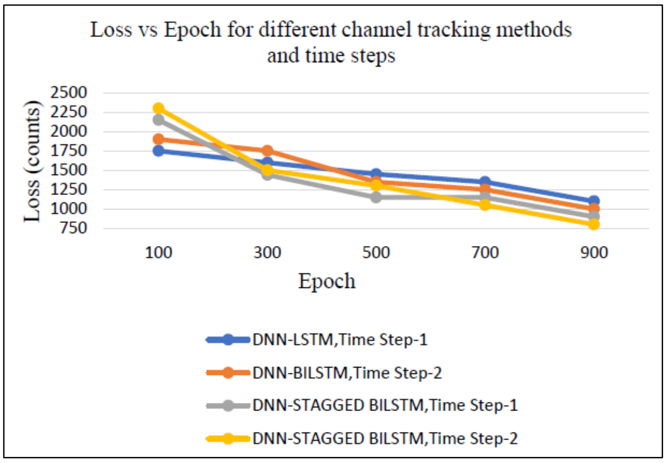

Fig. 5. Loss for channel tracking methods

Figure 5 compares the loss functions of several channel tracking techniques (LSTM, Bi-LSTM, and suggested algorithm). The channel sequence is configured with different historical time steps *T*=1 and 2 and is compared to the other two techniques, the suggested algorithm is capable of rapidly converging to loss near 0 for particular time periods in an interaction channel series. Thus, it enables loss near 0 by using the proposed algorithm. The recommended method still performs significantly better than other methods with smaller pilot overheads. The three different methodologies find the association over the time domain. Specifically, because of its simultaneous and stacked structure, our proposed method may extract facts not only from past events but also from the upcoming with deeper network structure.

7 Conclusion and future scope

In this study, we created the IRS-UAV-assisted communication system's dynamic channel model. The movements of mobile users and UAV navigation are taken into account when building the time-variant channel. In this study, we provide a demonstration of FL with IRS-UAV for channel tracking which includes two methods: pre-estimation of DNN channels and stacked Bi-LSTM. Specifically, the stacked Bi-LSTM system tracks historical data over time using a bidirectional framework spanning several stacked layers. Air-ground line-of-sight channels make UAV communications susceptible to listening in, despite the fact that UAV use is growing. This article's goal is to use IRSs to improve UAV communications and get around some of its issues and restrictions. Simulation results show that a proposed channel tracking strategy significantly outperforms different benchmarks with modest pilot overheads. This research work can be extended in the future by deploying another type of neural network and also, by doing the comparative analysis of IRS-DL-based UAVs and IRS-FL-based UAVs for various routing protocols.

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