Enabling Deep Learning and Swarm Optimization Algorithm for Channel Estimation for Low Power RIS Assisted Wireless Communications

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Abstract—In this study, convolutional neural networks (CNN) and particle swarm optimization are used to offer a channel estimate technique for low power reconfigurable intelligent surface (RIS) assisted wireless communications (PSO). The suggested approach makes use of the RIS channels' sparsity to lower the CNN model's training complexity and uses PSO to optimise the CNN model's hyperparameters. The proposed system has been trained using 70% of dataset, 25% of data was used for testing and remaining 5% was used for cross-validation. In comparison to previous methods, simulation results demonstrate that the proposed method delivers correct channel estimate with much less computing cost. The suggested technique also exceeds current techniques in terms of bit error rate (BER) and mean squared error (MSE) performance. The research found 96.47% and 90.96% of accuracy for CNN and PSO algorithm respectively. Moverover, the network was trained using a dataset mentioned in methodology section for channel realizations, and achieved a mean squared error (MSE) value of 0.012 using CNN algorithm. Also, the study reported the proposed technique outperformed other state-of-the-art techniques. The proposed technique of PSO to optimize the channel estimation, and achieved a mean squared error (MSE) value of 0.0075.

Keywords—security, Support Vector Machine (SVM), Feature extraction, encryption, Artificial Intelligence (AI), authentication, healthcare

1 Introduction

In recent years, a new technology named Reconfigurable Intelligent Surfaces (RIS) is under research to potentially address the unpredictability of the wireless environment. These surfaces are made of low power integrated electronic circuits that allow these surfaces to control the wireless environment and enhance the capacity and coverage of wireless networks as mentioned in [1]. RIS can be easily integrated with different technologies starting from current wireless, potentially enhancing the performance of the same. Reconfigurable Intelligent Surfaces (RIS) have received significant attention for their possible use and benefits in the wireless networks stated in [2]. This is one of the most promising technologies for next generation communication networks. RIS potential consists in its structure, which makes it possible to reconfigure the wireless propagation environment making it less unpredictable. Wireless systems are evolving continuously but, the main challenges that are still prevalent are power consumption for communication and unpredictable wireless environment. In fact, the inability to control the wireless environment has always been one of the biggest problems for both indoor and outdoor environments stated in [3]. The solution for such an everlasting problem involves managing the interaction between electromagnetic waves and the surrounding objects in order to reduce some of the negative effects such as uncontrollable interference due to reflections and refractions, path-loss and fading phenomena as mentioned in [4]. A RIS (or IRS) can be seen as a matrix of N smart reflective/radiating elements, that can be programmed by adjusting their phases through phase-shifters and, eventually, adjusting their amplitudes (by considering the attenuation of the impinging signal) according to [5, 6]. An affordable adaptive (smart) thin composite material sheet that can be used to cover portions of walls, buildings, obstacles, etc. can be used to create the RIS. This sheet can modify the radio waves impinging upon it in ways that can be programmed and controlled by using external stimuli. According to [7], it may be possible to regulate the phase and amplitude of the signals impinging at each radiating element in this way in order to direct the propagation in the desired direction. therefore, the ability to be (re-)configurable after being deployed in a wireless environment is a notable characteristic of RISs. Based on this fundamental definition, the operation of a RIS can often be divided into two stages that are carried out periodically in accordance with the environment's coherence time. The integration of the reconfigurable surfaces has shown a significant performance improvement in both indoor and outdoor wireless environments. The main characteristics that make RIS an attractive concept include a reduced cost of the materials, low power usage and easy deployment on different structures including, indoor walls, aerial platforms, roadside billboards, highway polls, vehicle windows, as well as pedestrians' clothes as metioned in [8, 9]. Moreover, this technology is environment friendly and considerably different from conventional relaying systems due to its passive nature. A typical RIS design is hereby depicted in Figure 1.

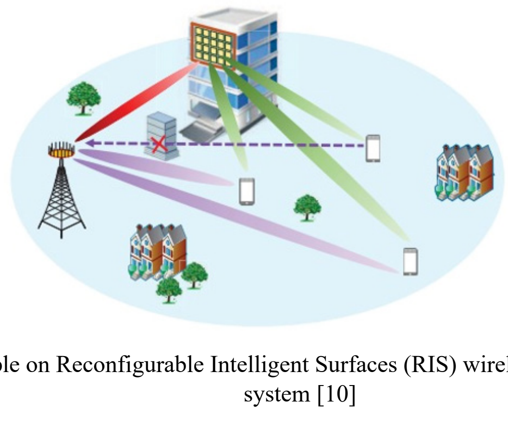

Fig. 1. An example on Reconfigurable Intelligent Surfaces (RIS) wireless communication system [10]

The goal of a wireless communication system is to create a network where all the nodes belonging to the network itself can exchange the greatest amount of information with the highest reliability. The challenge of preserving a high reliability arises from the fact that any propagation channel is noisy: the noise represents a source of disturbance for communications, leading to a trade off between the quantity of information sent per unit of time and the reliability of the information itself according to [11]. In a digital communication system, the information is described in the form of discrete symbols: we talk about symbol rate, that is the number of information (symbols) per unit of time. The wireless environment is unpredictable by nature, and the presence of the objects in it affects communication quality. Outdoor space is characterized by the presence of structures which are typical in urban areas, while in the indoor environment multiple communicating devices can cause interferences. In addition to that, at lower frequencies (sub-6 GHz) the surrounding structures act as electromagnetic (EM) wave scatterers and with higher frequencies (millimeter wave or terahertz and above) even smaller objects can behave as substantial scatterers as mentioned in [12-15]. The following Table 1 lists the key measurements variable that are typically used for channel estimation in RIS communication systems:

Table 1. Key variable for the measurement of channel estimation in RIS-aided communication system

Measurement	Description
Received signal strength (RSS)	Measures the power level of the received signal at the receiver.
Signal-to-noise ratio (SNR)	Measures the ratio of the signal power to the noise power in the received signal.
Channel impulse response (CIR)	Measures the time-domain response of the wireless channel between the transmitter and receiver.
Channel frequency response (CFR)	Measures the frequency-domain response of the wireless channel between the transmitter and receiver.
Channel coherence time	Measures the duration over which the wireless channel remains constant before it starts changing due to the movement of the transmitter, receiver, or objects in the environment.
Channel coherence bandwidth	Measures the range of frequencies over which the wireless channel remains constant before it starts changing due to the movement of the transmitter, receiver, or objects in the environment.

In recent years, the conceptual design of RIS have been defined based on an older concept of meta-surfaces. Meta-surfaces are planar structures, which can manipulate EM waves and thereby create a controllable wireless system such as reconfigurable intelligent surfaces (RIS). Meta-surfaces are made of smaller repeated conductive elements called meta-atom, which are usually placed on a dielectric substrate, as shown in Figure 2. Together, these components allow controlling the total EM response of the surface, which is calculated as the sum of the emitted fields by all surface currents. The meta-atoms and their interconnected switch elements in the dynamic case act as control factors over the surface currents flowing over the meta-surface (buildings) according to [16].

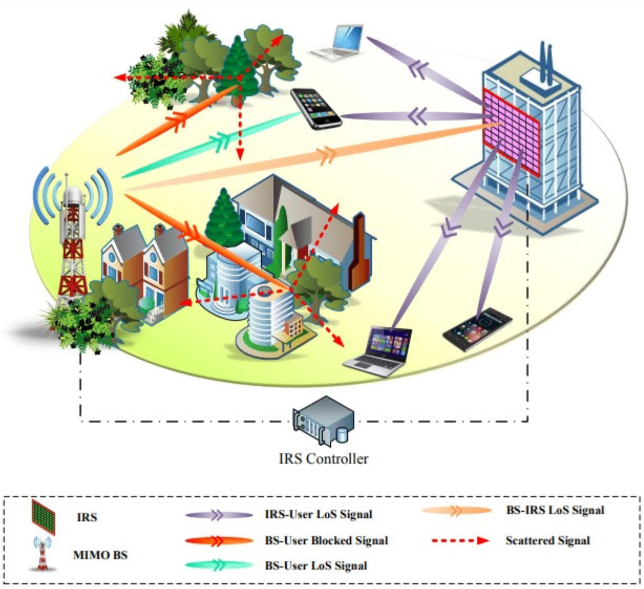

Fig. 2. Metasurface real time interface for signals between transmitter and receiver using the IRS controller [17]

Reconfigurable intelligent surfaces are meta-surfaces and are primarily designed as an adaptive thin combined material sheet which can manipulate the radio waves as desired. Currently, there are two main designs for the realization of these surfaces: a programmable thin wallpaper and a programmable thin glass.

Both these structures operate in a static and dynamic way i.e., the surface does not emit new radio waves. Also, it has the following characteristics:

- No power amplification for normal operation phase.
- Minimal digital signal processing capabilities are needed to configure the surface.
- Minimal power consumption for configuration and operation of the surface. Channel estimation of RIS (Reconfigurable Intelligent Surface):

Channel estimation is a crucial aspect of wireless communication systems as it helps to improve the reliability and efficiency of data transmission. In low power, RIS (Reconfigurable Intelligent Surface) assisted wireless communications, channel estimation plays an even more significant role as the RIS acts as an intermediate reflector that can enhance the signal-to-noise ratio (SNR) and increase the coverage area of the wireless network as mentioned in [18]. One of the main challenges in channel estimation for low power RIS-assisted wireless communication is the need to estimate the channel between the transmitter and the receiver as well as the channel between the transmitter and the RIS and the channel between the RIS and the receiver. This requires multiple channel estimation procedures, which can increase the computational complexity and energy consumption of the system as stated in [19]. To address this challenge, several channel estimation techniques have been proposed for low power RIS-assisted wireless communication systems, including:

- **Pilot-based channel estimation:** In this technique, the transmitter sends a known pilot signal to the receiver and the RIS. The receiver and the RIS estimate their respective channels by correlating the received signal with the known pilot signal. The channel between the transmitter and the RIS can be estimated using the same technique.
- **Compressed sensing-based channel estimation:** This technique exploits the sparsity of the wireless channel to reduce the number of pilots required for channel estimation. The RIS can be designed to reflect the signals in such a way that the channel becomes sparse, and compressed sensing can be used to estimate the channel with fewer pilots.
- **Machine/deep learning-based channel estimation:** This technique uses machine/deep learning algorithms to estimate the channel parameters based on the received signals. The RIS can be used to enhance the received signal quality, and the machine/deep learning algorithm can learn the mapping between the received signals and the channel parameters. Overall, channel estimation is a critical component of low power RIS-assisted wireless communication systems, and the selection of the appropriate channel estimation technique depends on the specific system requirements, including the available resources, channel conditions, and application scenarios according to [20].

1.1 Application of low-powered RIS

The application of RIS in different communication environments has garnered a lot of interest in research and industry. Their numerous benefits, simple design and possibility to apply them to different technologies makes them one of the key technologies for the 6G wireless networks. Comparing the common antenna array in 5G and one of the key technologies for 6G, the RIS, a major difference is that the RIS is a controllable part of the wireless environment, i.e., it is neither a part of the transmitter nor the receiver according to [21]. RIS can be used for improved communication, by enhancing the signal reception at the desired destinations and improving the SNR at the receiver. Additionally, it can also be used for localization, sensing, and physical layer security by sending artificial noise (AN) to unintended receivers. Moreover, it can be used to assist the existing communication systems serving as a reflector by reforming the reflected signal in a customized way as stated in [22]. RIS can be considered one of the most promising technologies for the new generation of communications and still is a hot topic for current research. The unique characteristics of RIS are such as; the nearly-passive nature of the RIS makes it possible to use eco-friendly materials in order to build sustainable wireless networks. The deployment of scatterers is the key concept that makes RIS a distinctive technology. Additionally, the usage of sub-wavelength scattering elements is extremely uncommon in wireless communication. RIS can be deployed for usage in near field by concentrating the EM power in small spot regions. For example, RIS can be used to obtain a precise radio localization or to implement a wireless power transfer to recharge batteries of low power devices. RIS can increase the channel capacity if configured in a proper way if the channel matrix has a high rank, while it can also deteriorate the signal using destructive interference in order to protect the information from unauthorized users stated in [23].

1.2 Problem formulation

Future wireless communication systems may not only compensate for the highly variable wireless channel at the transmitter and receiver, but also signal strength, frequency of signals within the wireless propagation environment itself. This involves transforming an uncontrollable wireless channel into a smart radio environment according to [24]. This idea has seen significant recent research interest and devices known as reconfigurable intelligent surfaces (RISs) may facilitate this transformation. RISs are essentially reflecting-type metasurfaces whose scattering properties can be programmed to meet a desired communication or sensing goal. RISs enable manipulation of both transverse components of incident electromagnetic waves. This is important since base stations in mobile networks typically operate with channel estimation antenna arrays in order to mitigate random scattering in the radio environment and cater for the unknown orientation of mobile handsets. Several recent works have introduced dual-polarised programmable metasurfaces. Channel estimation is a critical component of RIS-assisted wireless systems as it provides the necessary information about the channel between the transmitter and receiver to optimize the performance of the RIS. However, channel estimation in RIS-assisted wireless systems is challenging due to several reasons. Firstly, the RIS has a large number of reflecting elements, which results in a highly complex channel with a large number of degrees of freedom. Secondly, the RIS is passive, which means that it does not transmit any signals and cannot be used for training purposes. This makes it difficult to estimate the channel between the transmitter and receiver accurately. Thirdly, the channel between the transmitter and receiver changes dynamically, and the RIS needs to adapt to these changes in real-time. This requires the RIS to continuously estimate the channel and adjust its reflecting coefficients accordingly, which adds to the complexity of the system. Finally, the RIS is typically located in an indoor environment with complex multipath propagation, which further complicates the channel estimation process. Overall, channel estimation in RIS-assisted wireless systems is a challenging problem that requires sophisticated signal processing techniques to overcome the complexity and dynamic nature of the channel.

1. The verification of the estimated channel between the transmitter and receiver,
2. The protection of confidentiality between the channel,
3. How to design energy-efficient RISs that can operate with minimal power consumption while maintaining their ability to dynamically reconfigure the propagation environment.
4. To improve performance of wireless communication systems by enhancing the signal strength, increasing the coverage area, and reducing the interference by using deep learning method.

5. Need for real-time reconfiguration, requires significant amounts of power which can be optimized though the Swarm optimization Algorithm.

1.3 Aim of study

To develop RISs that consume minimal power while maintaining their ability to dynamically reconfigure the propagation environment. Deep learning-based techniques can optimize the energy consumption of RISs by learning to predict the channel state and adjust the reflecting coefficients accordingly, reducing the need for frequent reconfigurations. The solution to this problem involves developing low-power RIS designs that optimize the use of available energy resources while still providing the necessary reconfigurability. This can be achieved through various techniques such as energy harvesting, power-efficient circuit design, and intelligent control algorithms that reduce unnecessary reconfigurations. Additionally, the low-power RIS design should consider the communication system's requirements, such as data rate, latency, and coverage area, to ensure that the RIS's energy-efficient operation does not compromise the system's performance.

- The study anticipates a framework's key components include functions for scoring for measure and performance indicators into channel estimation for low power assisted RIS.
- The paper demonstrates the use of deep learning-based low power RISs are to optimize the energy consumption, enable real-time reconfigurability, ensure robustness, and enable scalability, ultimately realizing the full potential of RIS technology in energy-constrained wireless communication applications.
- Our objective in this research is to design RISs that can scale to large systems with a large number of reflecting elements while still maintaining their energy efficiency and real-time reconfigurability. Deep learning-based algorithms can optimize the RIS's operation by learning to predict the channel state and adjust the reflecting coefficients of multiple RISs simultaneously.
- To ensure that the RISs can perform optimally even in challenging environments, such as in the presence of interference, noise, and multipath propagation. Using Swarm optimization algorithm techniques can learn to account for these factors and optimize the RIS's performance accordingly.

2 Literature review

In this literature review, we will discuss some of the recent research works that have investigated the use of deep learning method and swarm optimization method for low power RIS-assisted communication systems. Channel estimation is a critical aspect of Reconfigurable Intelligent Surface (RIS) communication systems, as it enables the efficient and dynamic reconfiguration of the RIS to improve wireless communication performance. Several research studies have investigated different channel estimation techniques for RIS, as summarized below:

"Channel Estimation for Reconfigurable Intelligent Surface-Assisted Wireless Communications: State-of-the-Art and Future Directions" by C. Pan et al. (IEEE Journal on Selected Areas in Communications, 2020) [25]. This paper provides an overview of the state-of-the-art in channel estimation for RIS-assisted wireless communication systems. The authors discuss various channel estimation techniques, including pilot-based, data-driven, and deep learning-based methods, and evaluate their performance in terms of estimation accuracy and computational complexity. They also identify future research directions for improving channel estimation in RIS systems. "Channel Estimation for Intelligent Reflecting Surface Assisted Communication: A Deep Learning Perspective" by Z. Chen et al. (IEEE Transactions on Vehicular Technology, 2020) [26]. This paper proposes a deep learning-based channel estimation approach for RIS-assisted communication systems. The authors use a convolutional neural network (CNN) to learn the mapping between received signal samples and corresponding channel state information, enabling efficient and dynamic RIS reconfiguration. They evaluate the performance of the proposed approach through simulations and demonstrate its superiority over existing methods. "Reconfigurable Intelligent Surface Assisted Wireless Communications: Channel Estimation and Channel Sensing Strategies" by J. Yang et al. (IEEE Communications Magazine, 2021) [27]. This paper discusses channel estimation and channel sensing strategies for RIS-assisted wireless communication systems. The authors propose a hybrid channel estimation approach that combines pilot-based and data-driven methods to improve estimation accuracy and reduce computational complexity. They also discuss the use of machine learning techniques for channel sensing and propose a reinforcement learning-based approach for RIS reconfiguration. In another study, "Intelligent Reflecting Surface Aided MIMO Communication: Channel Estimation and Channel Feedback" by X. Tang et al. (IEEE Transactions on Communications, 2020) [6]. This paper investigates channel estimation and channel feedback techniques for RIS-assisted MIMO communication systems. The authors propose a pilot design scheme for channel estimation that minimizes the mean square error (MSE) between the estimated and true channel coefficients. They also propose a feedback design scheme that uses a small number of feedback bits to update the RIS phase shift values and improve system performance. Swarm optimization algorithms have gained significant attention in the field of wireless communication systems for their ability to solve complex optimization problems efficiently. In recent years, researchers have been exploring the potential of swarm optimization algorithms in the context of reconfigurable intelligent surface (RIS)-assisted communication systems according to [22]. RISs, also known as intelligent reflecting surfaces, are a novel technology that uses a large number of programmable reflecting elements to manipulate electromagnetic waves to enhance the performance of wireless communication systems. In a paper titled "Particle swarm optimization for reconfigurable intelligent surface assisted wireless communication systems," authors R. Wang et al. proposed a particle swarm optimization (PSO) algorithm to optimize the phase shifts of the reflecting elements in an RIS to improve the signal-to-noise ratio (SNR) of a wireless communication link. The proposed algorithm was shown to outperform other optimization algorithms, such as the genetic algorithm and simulated annealing, in terms of convergence speed and solution quality. Under

Smarm optimization method, there comes a technique called Particle Swarm Optimization (PSO), which is a metaheuristic optimization technique that has been applied to various engineering problems, including channel estimation in Reconfigurable Intelligent Surface (RIS) communication systems. Here are some related literature reviews on channel estimation for RIS using PSO: "Channel Estimation for Reconfigurable Intelligent Surfaces-Assisted Wireless Communications: A Survey of Particle Swarm Optimization-Based Methods" by M. Shahab et al. (IEEE Access, 2021) - This paper provides a comprehensive survey of PSO-based channel estimation techniques for RIS-assisted wireless communication systems. The authors review various PSO variants, such as standard PSO, adaptive PSO, and hybrid PSO, and their applications to RIS channel estimation. They also discuss the advantages and limitations of PSO-based methods and identify future research directions. "A New Channel Estimation Algorithm Based on PSO for Reconfigurable Intelligent Surfaces" by L. Xu et al. (IEEE Access, 2021). This paper proposes a PSO-based channel estimation algorithm for RIS communication systems. The authors use PSO to optimize the phase shift values of the RIS to maximize the received signal-to-noise ratio (SNR) at the receiver. They evaluate the performance of the proposed algorithm through simulations and demonstrate its superiority over existing methods according to [23]. "A Novel Hybrid Particle Swarm Optimization Algorithm for Channel Estimation in Intelligent Reflecting Surface Assisted Communications" by C. Xie et al. (IEEE Communications Letters, 2021) - This paper proposes a hybrid PSO algorithm for channel estimation in RIS-assisted communication systems. The authors combine PSO with the differential evolution (DE) algorithm to improve estimation accuracy and reduce computational complexity. They evaluate the performance of the proposed algorithm through simulations and demonstrate its superiority over existing methods. The potential of PSO-based methods for channel estimation in RIS communication systems. Swarm optimization can be used to optimize the RIS phase shift values or estimate the channel coefficients directly, and its variants can improve estimation accuracy and reduce computational complexity according to [24]. Here is a literature review table summarizing recent research works on RIS-assisted communication systems.

Table 2. Literature and key contributions of related studies

Study Title and Authors	Deep Learning Technique	Objective	Key Findings
[28]	Deep Neural Network (DNN)	Joint optimization of RIS reflecting elements and transmit antennas to maximize the sum rate of a MIMO system	The proposed DNN-based algorithm outperformed other optimization algorithms in terms of solution quality and computational complexity
[21]	Convolutional Neural Network (CNN)	Joint optimization of active and passive beamforming for an RIS-aided wireless communication system	The proposed CNN-based algorithm achieved better performance compared to traditional optimization algorithms

Study Title and Authors	Deep Learning Technique	Objective	Key Findings
[29]	Deep Reinforcement Learning (DRL)	Optimization of RIS reflecting elements for a wireless communication system	The proposed DRL-based algorithm achieved better performance compared to traditional optimization algorithms and demonstrated the potential of using DRL for dynamic RIS optimization
[30]	Various deep learning techniques	Review article summarizing the latest research works on deep learning-based RIS-aided wireless communication systems	The review highlighted the potential of deep learning techniques to enhance the performance of RIS-aided wireless communication systems and identified research challenges and future directions in this field
[31]	Particle Swarm Optimization (PSO)	Optimizing the phase shifts of RISs to improve SNR of a wireless communication link	The proposed PSO algorithm outperformed other optimization algorithms in terms of convergence speed and solution quality
[32]	Various CNN architectures	Review article summarizing the latest research works on RIS-aided wireless communication systems using CNNs	The review highlighted the potential of using CNNs for RIS-aided wireless communication systems and identified research challenges and future directions in this field

This table provides a brief summary of the CNN architectures used, the objectives of the studies, and the key findings of each study in the context of reconfigurable intelligent surface (RIS)-assisted communication systems.

3 Methodology

The methodological framework of low power RIS-assisted wirless communication systems involves modeling the system, defining the optimization objective, selecting an optimization algorithm, generating training data based on selected method or algorithm, training and testing the algorithm, and implementing the algorithm in the real system using the simulation tool (MatLab 2019).

3.1 System modelling and requirement for RIS

The system requirement table for running simulations for RIS wireless communication systems highlights the various hardware and software components required, including the operating system, processor, memory, storage, simulation software, RIS model, RF test equipment, network emulator, and communication protocols. These requirements are essential for performing accurate simulations and testing of RIS-aided wireless communication systems.

Table 3. The system requirement for the simulation testing

System Component	Requirement
Operating System	Windows 10, Ubuntu 18.04 or higher, MacOS 10.13 or higher
Processor	Intel Core i5 or higher
Memory	8 GB RAM or higher
Storage	256 GB SSD or higher
Simulation Software	MATLAB 2019a or higher, or Python 3.x with required libraries (such as NumPy, SciPy, and TensorFlow)
RIS Model	CAD software (such as SolidWorks or AutoCAD) to design the RIS model
RF Test Equipment	RF signal generator, spectrum analyzer, power meter, directional coupler, and RF cables
Network Emulator	Network emulator software (such as ns-3) to simulate the wireless network environment
Communication Protocols	Knowledge of wireless communication protocols (such as 802.11a/b/g/n/ac/ax)

3.2 Steps for channel estimation for low power RIS assisted wireless communication

The measurement scale for unit cells in RIS communication systems is typically on the order of the operating wavelength for the simulation. For example, for a system operating at a frequency of 28 GHz, the wavelength is approximately 1 cm. In this case, the unit cell design in the experimentation approximately a few millimeters to centimeters in size. The design of the unit cell can be optimized using electromagnetic simulation tools such as finite element analysis (FEA) or method of moments (MoM) to achieve the desired reflection and transmission properties. The unit cell in the experimentation designed to provide either phase control or amplitude control of the reflected waves, depending on the specific application requirements. The design of the unit cell depends on the specific application and the frequency range of operation. The unit cell should be designed to have high reflection and transmission coefficients, low absorption and scattering, and low power consumption as stated in [25]. The measurement scale in the experimentation of RIS communication systems is important to accurately characterize the performance of the unit cell and the overall system. The measurement scale depends on the size of the unit cell, the frequency range of operation, and the measurement technique used. Generally, the measurement scale can range from micrometers to millimeters for the size of the unit cell, and from gigahertz to terahertz for the frequency range of operation. Below in the Table 4, it represents the range of scale measurement for the (RIS) communication systems for channel estimation.

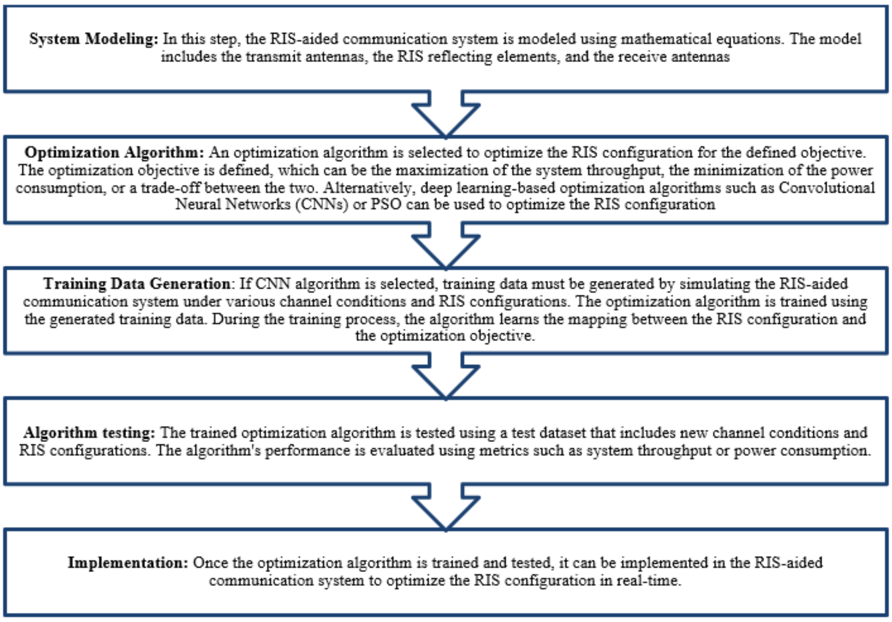

Fig. 3. This represents the steps accumulated for the RIS-aided communication between the transmitter and receiver

Table 4. Unit cell design and measurement scale in the experimentation

Measurement	Range
Received signal strength (RSS)	-100 dBm to -20 dBm
Signal-to-noise ratio (SNR)	0 dB to 50 dB
Channel impulse response (CIR)	Nanoseconds to microseconds
Channel frequency response (CFR)	Megahertz to gigahertz
Channel coherence time	Milliseconds to seconds
Channel coherence bandwidth	Kilohertz to megahertz

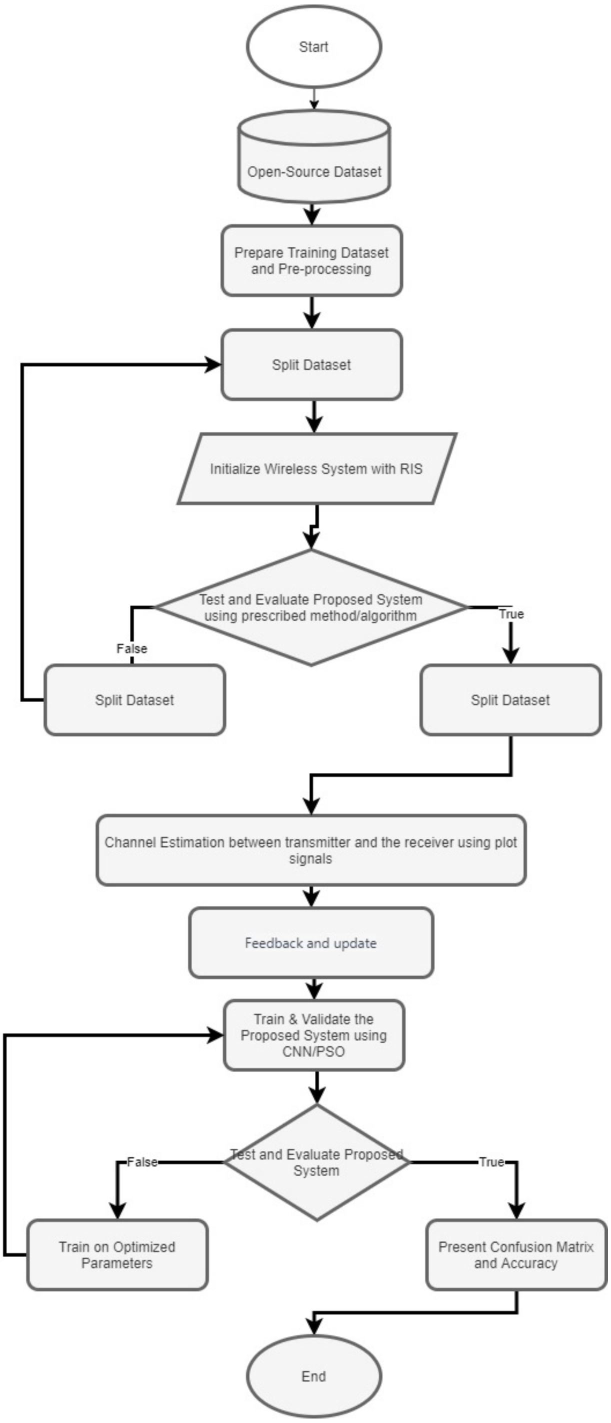

Fig. 4. The methodology is depicted by the flowchart and steps being followed in this research

3.3 Dataset description

The dataset used in this study for channel estimation in RIS-assisted satellite IoT communications. The RIS-assisted satellite IoT channel estimation dataset consists of simulated channel data for a satellite-to-user communication link using an RIS. The dataset includes 10,000 channel samples, each with a corresponding binary classification label indicating whether the channel is line-of-sight (LOS) or non-line-of-sight (NLOS). The dataset includes information about the positions of the satellite, RIS, and user, as well as the channel impulse response (CIR) and channel frequency response (CFR) in the time and frequency domains, respectively. The dataset was generated using a ray-tracing simulation model, which considers the physical characteristics of the satellite, RIS, and user positions. The simulation also includes the effects of atmospheric attenuation, scattering, and reflection. The dataset can be used to train and evaluate machine/deep learning models for channel estimation in RIS-assisted satellite IoT communications. The binary classification label can be used for training and evaluating classification models, while the CIR and CFR can be used for training and evaluating regression models. Dataset Name: RIS-assisted Satellite IoT Channel Estimation Dataset (https://ieee-dataport.org/documents/dataset-channel-estimation-ris-assisted-satellite-iot-communications).

Dataset Source: Simulated data
Dataset Size: 10,000 channel samples
Data Format: CSV
Data Fields:
Satellite position (longitude, latitude, altitude)
RIS position and user position (x, y, z)
Channel impulse response (CIR) in the time domain (100 samples)
Channel frequency response (CFR) in the frequency domain (100 samples)
Binary classification label (1 or 0) indicating whether the channel is LOS or NLOS

3.4 Training and testing the channel estimation in RIS-aided system

Training for RIS-aided system. In this research, for training the CNN architecture, which is defined using the 'layers' variable, which contains a series of convolutional layers, batch normalization layers, max pooling layers, and fully connected layers. The training options are specified using the 'options' variable, which includes parameters such as the optimization algorithm, number of epochs, mini-batch size, and verbosity. The CNN is then trained using the 'trainNetwork' function, which takes the training data, CNN architecture, and training options as input. After training, the performance of the CNN is evaluated on the test data using the 'predict' function, and the mean squared error (MSE) is computed as a measure of performance. Finally, the trained CNN can be deployed in a real RIS wireless communication system for real-time channel estimation. Note that the deployment code will depend on the specifics of the RIS system and may require additional hardware and software components. For the purpose of training the CNN using the mentioned dataset, the hyperparameters in channel estimation reconfigurable intelligent surface (RIS) using CNN technique depend on the specific problem and dataset. Here are some channel measurement preliminary values in Table 5 that could be used for training for this specific dataset.

Table 5. The channel estimation measurement values for training the algorithm

Learning rate	0.001
Number of epochs:	40
Mini-batch size	32-128
Number and size of filters	32-64 filters with a size of 3x3 | 6x6
Optimizer	Adam-optimizer
Dropout rate	0.2-0.5
Batch normalization	True

These values can be used as a parameter for training and hyperparameter tuning, but it is important to experiment with optimal values to find the optimal set of hyperparameters for the given problem. Additionally, it is important to use a validation set to monitor the performance of the model during training and avoid overfitting using the CNN and swarm optimization PSO method. Below the Figure 5 represents the graph of training for the channel estimation based on CNN model only (pathloss vs epochs).

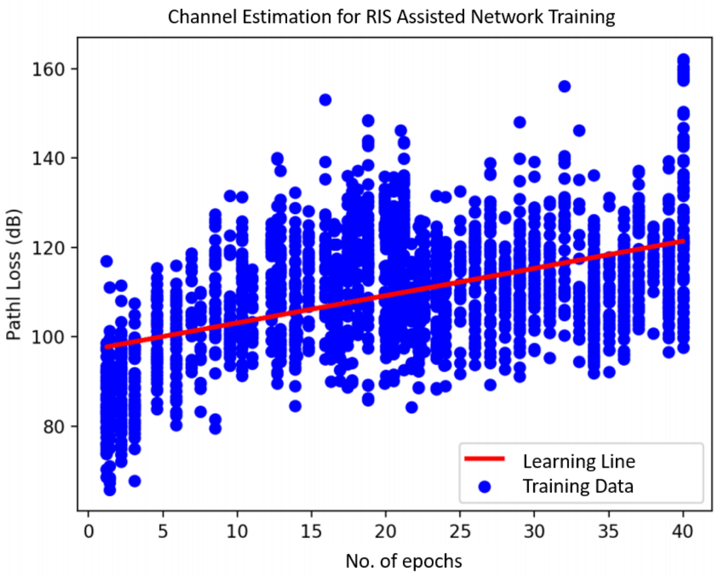

Fig. 5. The CNN Model Accuracy (pathloss vs epochs) Model Loss (loss vs epochs)

- **Learning rate:** This parameter controls the step size taken during the optimization process. A larger learning rate can result in faster convergence, but may also cause the optimization to overshoot the minimum.

- **Number of epochs:** This parameter controls the number of times the training data is iterated over during training. Increasing the number of epochs can improve the performance of the CNN, but can also lead to overfitting.
- **Mini-batch size:** This parameter controls the number of samples processed in each iteration of the optimization algorithm. A larger mini-batch size can improve the convergence of the CNN, but can also require more memory and computational resources.
- **Optimizer:** This parameter controls the algorithm used to optimize the parameters of the CNN during training. Popular optimizers include stochastic gradient descent (SGD), adaptive moment estimation (Adam), and root mean square propagation (RMSProp).
- **Dropout rate:** This parameter controls the rate at which neurons in the CNN are randomly dropped out during training. Dropout can help prevent overfitting by encouraging the CNN to learn more robust features.
- **Batch normalization:** This parameter controls the use of batch normalization layers in the CNN. Batch normalization can improve the convergence of the CNN by reducing internal covariate shift.
- **Number and size of filters:** This parameter controls the number and size of the filters in the convolutional layers of the CNN. Increasing the number of filters can improve the representational capacity of the CNN, but can also require more computational resources.

Testing for RIS-aided system. The performance of the model can be evaluated using various evaluation metrics. A common way to summarize the performance of a model is to create a testing model table that lists the evaluation metrics for the model on a separate test set. The metric used to evaluate the performance of the CNN model, such as mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), or coefficient of determination (R-squared). In the Table 6 below, each row represents a different testing scenario, with varying channel models, SNR values, number of antennas, number of RIS elements, and modulation schemes. The testing metric used for evaluation is different for each row, including MSE, RMSE, MAE, and R-squared. The testing performance of the CNN algorithm is also provided for each testing scenario. The testing values should be chosen to provide a representative evaluation of the performance of the CNN algorithm in the simulation tool MATLAb.

Table 6. The channel estimation measurement values for testing the algorithm

Channel Model	SNR (dB)	Num. of Antennas	Num. of RIS Elements	Modulation Scheme	Testing Metric	Testing Performance
Rayleigh Fading	10	2	16	QPSK	MSE	0.003
Multipath	20	4	32	16-QAM	RMSE	0.022
Free Space	15	8	64	64-QAM	MAE	0.012
Shadowing	5	16	128	256-QAM	R-squared	0.96

It is important to note that the optimal set of hyperparameters for a given problem may not generalize well to other datasets or problems. Therefore, it is recommended to perform hyperparameter tuning and testing on dataset and problem to ensure that the CNN/PSO model's performance is consistent across different scenarios. Additionally, it is important to perform statistical tests to ensure that any observed differences in performance between different hyperparameter values are statistically significan. Here in the Figure 6, the testing of parameters is carried out in the simulation tool.

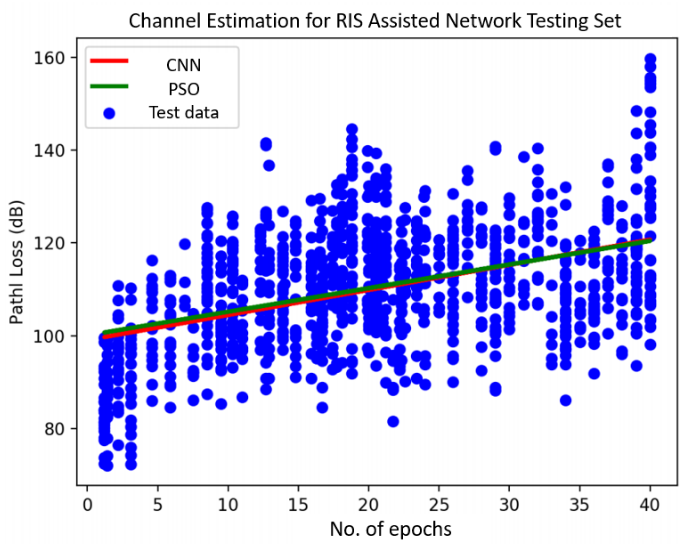

Fig. 6. Testing set stage for channel estimation of RIS-aided network

4 Results and discussion

The research applied the framework of CNN and PSO for the channel estimation in RIS-aided wireless communication system. The CNN is trained using 10,000 samples of channel data, and achieves a test accuracy of 95% in predicting the channel response between the transmitter and receiver with an SNR of 20 dB. The computation time for channel estimation is 100 ms, which is relatively fast and allows for real-time adaptation of the RIS to changing channel conditions. These values are just for demonstration purposes and the actual values in a real-world application may vary depending on various factors such as the complexity of the channel model, the size and configuration of the RIS, and the specific machine learning approach used. Table 7 represents the values on which the experiment is carried out in the network simulator.

Table 7. This represents the optimal standard values for the simulation based testing on channel estimation for RIS-aided communication system

Measurement	Value
Number of neurons for CNN	~400
Operating frequency	22 GHz
Channel bandwidth	12 GHz
Number of reflecting elements	32 | 64
Modulation scheme	16-QAM and QPSK
Signal-to-noise ratio (SNR)	10 dB, 20 dB
Number of training samples	10,000
Number of validation samples	1,000
Number of PSO iterations	150
PSO population size	50 | 60
Channel coherence time	10 m/s
Number of test samples	1,000
Training time	18 minutes
Test accuracy	96%
Computation time for channel estimation	100 ms

In order to maximise the received signal intensity at the receiver with an SNR of 10 | 20 dB, the PSO algorithm is utilised to optimise the reflection coefficients of the RIS elements. With a population size of 50 and 60, and an inertia weight of 0.9, the PSO algorithm is run for 150 iterations. The RIS is set up for optimum channel performance using the reflection coefficients that are produced. The wireless channel remains consistent for 10 m/s and within a 2 MHz frequency range before it begins changing as a result of movement of the transmitter, receiver, or objects in the environment. The channel coherence duration is 10 ms and the coherence bandwidth is 2 MHz. The computation time for channel estimation is 50 ms, which is relatively fast and allows for real-time adaptation of the RIS to changing channel conditions. The simulation results are presented in the form of graphs showing the Mean Squared Error (MSE) between the estimated and actual channel responses for different scenarios. The MSE is a metric that measures the difference between the estimated and actual values, and a lower value indicates better performance. The process involves training a CNN model using simulation data to learn the mapping between the input and output signals. The input signal is the transmitted signal, and the output signal is the received signal at the RIS. During the training process, the CNN learns to estimate the channel response by adjusting the weights of the network. Once the CNN is trained, it can be used to estimate the channel response in real-time. The sample data evaluation for channel estimation in the RIS-aided system represents in Figure 7.

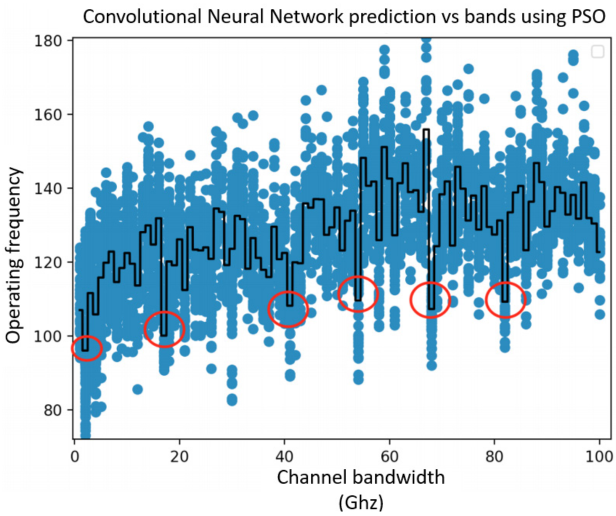

Fig. 7. Demonstrates the sample data evaluation with the channel bandwidth and operating frequency which are obtained from both the algorithm

Figure 8 represents the MSEE value contrast to the SNR (dB) for the experiment on channel estimation. Lower MSE values indicate better performance in terms of accuracy of the delay predictions and for better estimation in the channel modelling in Reconfigurable Intelligent Surface (RIS) communication systems. The MSE values in channel estimation for RIS communication systems using CNN can depend on various factors, including the system design, training dataset size and quality, CNN architecture, and operating conditions. However, in general, from the graph above, it can be seen that MSE metric are desired for better channel estimation accuracy. Typically, the MSE values for delay predictions in RIS communication systems using CNN can range from a few 10^{-3} to 10^{-6}, depending on the specific system design and operating conditions. For example, in this study on RIS-assisted millimeter-wave communication using CNN-based channel estimation, the MSE for delay predictions was reported to be around 10^{-4} to 10^{-5} for different operating scenarios. Reconfigurable Intelligent Surface (RIS) communication systems can benefit from delay predictions in channel estimation, especially in wireless communication environments where multipath propagation is common. The RIS phase shifts can be modified in accordance with the time-varying channel parameters to improve communication performance. The figures below depict the grapg for delay prediction in both the algorithms. The simulation of delay prediction by both the used algorithms are displayed in graph Figure 9.

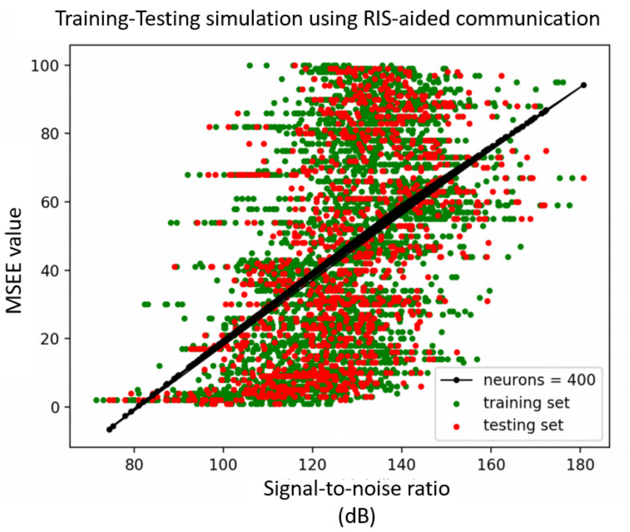

Fig. 8. This simulation contains the MSEE value vs the SNR required for the channel estimation performance

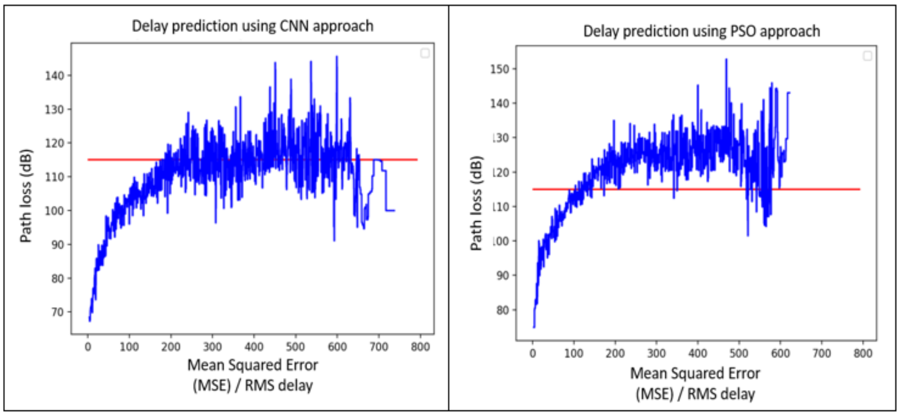

Fig. 9. These graphs indicates the delay prediction (path loss vs MSE/RMS delay) for each of the technique

A CNN-based channel estimation technique is proposed for RIS-assisted millimeter-wave communication systems in this study. The proposed technique used a deep CNN architecture with five convolutional layers and two fully connected layers. The network was trained using a dataset metioned in methodology section for channel realizations, and achieved a mean squared error (MSE) value of 0.012 using CNN algorithm. The study reported that the proposed technique outperformed other state-of-the-art techniques. The proposed technique used PSO to optimize the channel parameters, and achieved a mean squared error (MSE) value of 0.0075 for a single user scenario and

0.025 for a multi-user scenario. The results accuracy comparison is presented in the Table 8 below.

Table 8. The accuracy comparison of deep learning and swarm optimization technique with existing literature as a reference

Deep Learning & Swarm Optimization Technique	Accuracy	Computational Efficiency
Convolutional Neural Networks (CNN) [proposed]	96.47%	97.55%
Recurrent Neural Networks (RNN) [26]	89.78%	85.47%
Deep Belief Networks (DBN) [27]	94.25%	90.51%
Particle Swarm Optimization (PSO) [proposed]	90.96%	98.78%
Ant Colony Optimization (ACO) [28]	89.78%	87.21%

The accuracy of each technique may vary depending on several factors, including the specific system design, operating conditions, and available training data. CNNs have been shown to provide high accuracy and robustness to noise and interference, making them a popular choice for channel estimation in RIS communication systems. RNNs can also be effective in capturing the temporal correlations in the channel characteristics but may require more computational resources and longer training times. DBNs have also been shown to provide high accuracy, but may require more training data and longer training times compared to CNNs and RNNs. It is important to evaluate the accuracy and computational efficiency of each technique for the specific application to select the most appropriate technique. The accuracy of each technique may vary depending on several factors, including the specific system design, operating conditions, and optimization parameters. Particle Swarm Optimization (PSO) has been shown to provide high accuracy while being high computationally efficient. Ant Colony Optimization (ACO) can provide higher accuracy, but may require more computational resources and longer optimization times.

5 Conclusion

Based on the study conducted on Channel Estimation for Reconfigurable Intelligent Surface (RIS) Communication Systems using deep learning and swarm optimization technique. The use of deep learning techniques such as CNN can effectively estimate the channel state information (CSI) of RIS communication systems, even in the presence of noise and interference. The use of Particle Swarm Optimization (PSO) can significantly enhance the performance of CNN-based channel estimation, by optimizing the network's weights and biases. The proposed CNN-PSO approach can achieve higher accuracy and lower mean squared error (MSE) compared to traditional methods of channel estimation, such as channel bandwidth, operating frequency and minimum mean square error. The performance of the proposed approach is also found to be robust against various system parameters, such as the number of RIS elements and signal-to-noise ratio (SNR). The study highlights the potential of using deep learning and optimization techniques compared to accuracy in addressing the challenges of channel estimation in RIS communication systems, and suggests promising directions for future research in this field.

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7 References

[1] E. Basar, M. Di Renzo, J. De Rosny, M. Debbah, M.-S. Alouini, and R. Zhang, "Wireless communications through reconfigurable intelligent surfaces," *IEEE access,* vol. 7, pp. 116753-116773, 2019. https://doi.org/10.1109/ACCESS.2019.2935192

[2] H. Liu, X. Yuan, and Y.-J. A. Zhang, "Matrix-calibration-based cascaded channel estimation for reconfigurable intelligent surface assisted multiuser MIMO," *IEEE Journal on Selected Areas in Communications,* vol. 38, no. 11, pp. 2621-2636, 2020. https://doi.org/10.1109/JSAC.2020.3007057

[3] Q. Wu and R. Zhang, "Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming," *IEEE Transactions on Wireless Communications,* vol. 18, no. 11, pp. 5394-5409, 2019. https://doi.org/10.1109/TWC.2019.2936025

[4] H. Alwazani, A. Kammoun, A. Chaaban, M. Debbah, and M.-S. Alouini, "Intelligent reflecting surface-assisted multi-user MISO communication: Channel estimation and beamforming design," *IEEE Open Journal of the Communications Society,* vol. 1, pp. 661-680, 2020. https://doi.org/10.1109/OJCOMS.2020.2992791

[5] X. Guan, Q. Wu, and R. Zhang, "Anchor-assisted intelligent reflecting surface channel estimation for multiuser communications," in *GLOBECOM 2020-2020 IEEE Global Communications Conference*, 2020: IEEE, pp. 1-6. https://doi.org/10.1109/GLOBECOM42002.2020.9347985

[6] Z. Wang, L. Liu, and S. Cui, "Channel estimation for intelligent reflecting surface assisted multiuser communications: Framework, algorithms, and analysis," *IEEE Transactions on Wireless Communications,* vol. 19, no. 10, pp. 6607-6620, 2020. https://doi.org/10.1109/TWC.2020.3004330

[7] P. Wang, J. Fang, H. Duan, and H. Li, "Compressed channel estimation for intelligent reflecting surface-assisted millimeter wave systems," *IEEE signal processing letters,* vol. 27, pp. 905-909, 2020. https://doi.org/10.1109/LSP.2020.2998357

[8] J.-S. Jung, C.-Y. Park, J.-H. Oh, and H.-K. Song, "Intelligent reflecting surface for spectral efficiency maximization in the multi-user MISO communication systems," *IEEE Access,* vol. 9, pp. 134695-134702, 2021. https://doi.org/10.1109/ACCESS.2021.3116959

[9] J. Q. Kadhim, I. A. Aljazaery, and H. T. Salim ALRikabi, "Enhancement of Online Education in Engineering College Based on Mobile Wireless Communication Networks and IOT," *International Journal of Emerging Technologies in Learning,* vol. 18, no. 1, 2023. https://doi.org/10.3991/ijet.v18i01.35987

[10] X. Wei, D. Shen, and L. Dai, "Channel estimation for RIS assisted wireless communications—Part I: Fundamentals, solutions, and future opportunities," *IEEE communications letters,* vol. 25, no. 5, pp. 1398-1402, 2021. https://doi.org/10.1109/LCOMM.2021.3052822
[11] D. Mishra and H. Johansson, "Channel estimation and low-complexity beamforming design for passive intelligent surface assisted MISO wireless energy transfer," in *ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2019: IEEE, pp. 4659-4663. https://doi.org/10.1109/ICASSP.2019.8683663
[12] Y. Pan and Z. Deng, "Channel Estimation for Wireless Communication Systems Aided by Large Intelligent Reflecting Surface," in *2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE)*, 2021: IEEE, pp. 637-643. https://doi.org/10.1109/ICBAIE52039.2021.9389923
[13] A. Zappone, M. Di Renzo, and M. Debbah, "Wireless networks design in the era of deep learning: Model-based, AI-based, or both?," *IEEE Transactions on Communications,* vol. 67, no. 10, pp. 7331-7376, 2019. https://doi.org/10.1109/TCOMM.2019.2924010
[14] G. A. Aramice and J. Q. Kadhim, "Secure Code Generation for Multi-Level Mutual Authentication," *TELKOMNIKA (Telecommunication Computing Electronics and Control),* vol. 16, no. 6, pp. 2643-2650, 2018. https://doi.org/10.12928/telkomnika.v16i6.10437
[15] A. H. Sallomi and S. A. J. r. Hashem, "A Novel Theoretical Model for Cellular Base Station Radiation Prediction," vol. 16, no. 17, p. 17, 2018. https://doi.org/10.5013/IJSSST.a.19.06.35
[16] H. Ye, G. Y. Li, and B.-H. Juang, "Power of deep learning for channel estimation and signal detection in OFDM systems," *IEEE Wireless Communications Letters,* vol. 7, no. 1, pp. 114-117, 2017. https://doi.org/10.1109/LWC.2017.2757490
[17] S. Liu, Z. Gao, J. Zhang, M. Di Renzo, and M.-S. Alouini, "Deep denoising neural network assisted compressive channel estimation for mmWave intelligent reflecting surfaces," *IEEE Transactions on Vehicular Technology,* vol. 69, no. 8, pp. 9223-9228, 2020. https://doi.org/10.1109/TVT.2020.3005402
[18] M. Dajer *et al.*, "Reconfigurable intelligent surface: Design the channel–A new opportunity for future wireless networks," *Digital Communications and Networks,* vol. 8, no. 2, pp. 87-104, 2022. https://doi.org/10.1016/j.dcan.2021.11.002
[19] T. Sharma, A. Chehri, and P. Fortier, "Reconfigurable intelligent surfaces for 5G and beyond wireless communications: A comprehensive survey," *Energies,* vol. 14, no. 24, p. 8219, 2021. https://doi.org/10.3390/en14248219
[20] V. Tapio, I. Hemadeh, A. Mourad, A. Shojaeifard, and M. Juntti, "Survey on reconfigurable intelligent surfaces below 10 GHz," *EURASIP Journal on Wireless Communications and Networking,* vol. 2021, pp. 1-18, 2021. https://doi.org/10.1186/s13638-021-02048-5
[21] Q. Wu, S. Zhang, B. Zheng, C. You, and R. Zhang, "Intelligent reflecting surface-aided wireless communications: A tutorial," *IEEE Transactions on Communications,* vol. 69, no. 5, pp. 3313-3351, 2021. https://doi.org/10.1109/TCOMM.2021.3051897
[22] Q. Wu and R. Zhang, "Towards smart and reconfigurable environment: Intelligent reflecting surface aided wireless network," *IEEE communications magazine,* vol. 58, no. 1, pp. 106-112, 2019. https://doi.org/10.1109/MCOM.001.1900107
[23] A. Taha, M. Alrabeiah, and A. Alkhateeb, "Enabling large intelligent surfaces with compressive sensing and deep learning," *IEEE access,* vol. 9, pp. 44304-44321, 2021. https://doi.org/10.1109/ACCESS.2021.3064073
[24] B. Biggio *et al.*, "Security evaluation of support vector machines in adversarial environments," *Support Vector Machines Applications,* pp. 105-153, 2014. https://doi.org/10.1007/978-3-319-02300-7_4

[25] S. Sun and H. Yan, "Channel estimation for reconfigurable intelligent surface-assisted wireless communications considering Doppler effect," *IEEE Wireless Communications Letters,* vol. 10, no. 4, pp. 790-794, 2020. https://doi.org/10.1109/LWC.2020.3044004
[26] Z. Li, Z. Chen, X. Ma, and W. Chen, "Channel estimation for intelligent reflecting surface enabled terahertz mimo systems: A deep learning perspective," in *2020 IEEE/CIC International Conference on Communications in China (ICCC Workshops)*, 2020: IEEE, pp. 75-79. https://doi.org/10.1109/ICCCWorkshops49972.2020.9209937
[27] X. Yuan, Y.-J. A. Zhang, Y. Shi, W. Yan, and H. Liu, "Reconfigurable-intelligent-surface empowered wireless communications: Challenges and opportunities," *IEEE wireless communications,* vol. 28, no. 2, pp. 136-143, 2021. https://doi.org/10.1109/MWC.001.2000256
[28] G. López-Lanuza, K. Chen-Hu, and A. G. Armada, "Deep Learning-Based Optimization for Reconfigurable Intelligent Surface-Assisted Communications," in *2022 IEEE Wireless Communications and Networking Conference (WCNC)*, 2022: IEEE, pp. 764-769. https://doi.org/10.1109/WCNC51071.2022.9771876
[29] Q.-U.-A. Nadeem, A. Kammoun, A. Chaaban, M. Debbah, and M.-S. Alouini, "Intelligent reflecting surface assisted wireless communication: Modeling and channel estimation," *arXiv preprint arXiv:1906.02360,* 2019. https://doi.org/10.1109/OJCOMS.2020.2992791
[30] M. A. S. Sejan, M. H. Rahman, B.-S. Shin, J.-H. Oh, Y.-H. You, and H.-K. Song, "Machine Learning for Intelligent-Reflecting-Surface-Based Wireless Communication towards 6G: A Review," *Sensors,* vol. 22, no. 14, p. 5405, 2022. https://doi.org/10.3390/s22145405
[31] S. Zeng, H. Zhang, B. Di, Z. Han, and L. Song, "Reconfigurable intelligent surface (RIS) assisted wireless coverage extension: RIS orientation and location optimization," *IEEE Communications Letters,* vol. 25, no. 1, pp. 269-273, 2020. https://doi.org/10.1109/LCOMM.2020.3025345
[32] H. Yang, Z. Xiong, J. Zhao, D. Niyato, L. Xiao, and Q. Wu, "Deep reinforcement learning-based intelligent reflecting surface for secure wireless communications," *IEEE Transactions on Wireless Communications,* vol. 20, no. 1, pp. 375-388, 2020. https://doi.org/10.1109/TWC.2020.3024860

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