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Review article

A review on machine learning and deep learning for various antenna design applications

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ABSTRACT

The next generation of wireless communication networks will rely heavily on machine learning and deep learning. In comparison to traditional ground-based systems, the development of various communication-based applications is projected to increase coverage and spectrum efficiency. Machine learning and deep learning can be used to optimize solutions in a variety of applications, including antennas. The latter have grown popular for obtaining effective solutions due to high computational processing, clean data, and large data storage capability. In this research, machine learning and deep learning for various antenna design applications have been discussed in detail. The general concept of machine learning and deep learning is introduced. However, the main focus is on various antenna applications, such as millimeter wave, body-centric, terahertz, satellite, unmanned aerial vehicle, global positioning system, and textiles. The feasibility of antenna applications with respect to conventional methods, acceleration of the antenna design process, reduced number of simulations, and better computational feasibility features are highlighted. Overall, machine learning and deep learning provide satisfactory results for antenna design.

1. Introduction

Machines are developing the abilities of humans, such as problem solving, decision-making, and learning. ML automates analytical model building through data analysis. On the other hand, DL is an ML skill that helps machines mimic human behavior by processing data. Through using ML and DL, many applications can gain an advantage, and the antenna is one of them. As the complexity of antennas increases, ML and DL are used to optimize the performance of the antennas. ML and DL have been used to create multiple trained models for antenna design applications, allowing antenna design applications to become more efficient and rapid. With the help of high computing power and software engineering capabilities, ML and DL for different antenna designs have become the most important fields of recent research. Millimeter wave, body-centric, terahertz, satellite, UAV, GPS, and textile are just a few of the antenna design topics. Body-centric is human to human communication with the assistance of wearable antennas. Terahertz frequencies are used for spectroscopy in different areas. Satellites are objects that orbit around the earth and send communication signals. UAVs are aircraft with ground-based control, and textile technology focuses on textile fabric made from textile fibers.

Without the utilization of machine learning and deep learning algorithms, antenna design is hard to design and maintain. There is a problem with acceleration in antenna design without ML and DL. Maintaining low errors and high productivity is difficult without ML and DL. Without the support of DL and ML reduction in simulation, preserving work feasibility and calculation of antenna behavior is a very hard job to do.

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In this section, the authors introduce all the applications for various antenna design fields by using ML and DL. Firstly, in [1], To increase the mean data rate of a multi-antenna wireless system and implement hybrid beam forming in mmWave frequency bands, a Reinforcement Learning (RL) algorithm was used to speed up the selection process of spatial beams. RL is an area of ML used to maximize the notion of growing reward. In [7], taking maximum advantage of ML with previous beam training information using locations, nearest vehicles, and sizes of the receiver were used to learn the optimal beam pair index. For research into mmWave or massive MIMO antennas, a dataset is needed, so in [18], the dataset for mmWave or massive MIMO antennas has been described. In [19], authors describe a hybrid beam forming (BF) design for the downlink of multi-user mmWave systems, in which the number of AEs used at the base station to achieve BF benefits per user is proportional to the user's distance. A machine learning framework for learning environment-aware beam-forming codebooks for large-scale MIMO systems was developed. In [25], authors provide an overview of millimeter wave channel concepts as well as an explanation of how map-based channels are classified. In [34], a system for future body-centric communication was developed using off-the-shelf non-wearable devices such as Wi-Fi routers, network interfaces, and an omnidirectional antenna. In [25], authors provide an overview of millimeter wave channel models as well as an indication of how map-based channels are classified. A THz DL computing Tomography (CT) system is presented in section [37], capable of visualizing hidden objects using a variety of material systems. A ML model Support Vector Machine (SVM) was used to design and optimize reflect arrayantennas. To simplify feasible beam hopping (BH) in multibeam satellite systems, a Dl-based path was developed in [47]. A full description of the ML design, the design of collectors and relays, and a brief description of the choice of UAV types have been given in section [73]. A machine learning-based hybrid framework for propagating both aleatory and epistemic uncertainties in antenna design is proposed in [78]. In [93], a neural network (NN) dependent delay locked loop (DLL) is established in the GPS receiver for multipath reduction. An overview of the applications of machine learning and deep learning to the development of various antenna designs has been presented in this paper. The used methods and their outcomes have been presented. A comprehensive review of different antenna designs, the general concept of machine learning and deep learning, and ways of electromagnetic computation are also studied in this paper.

The paper is structured in the following way-Section 1 introduces the topic, Section 2 discusses machine learning and deep learning for various antenna design applications, Section 3 discusses analysis, and Section 4 concludes the presented study.

2. Machine learning and deep learning for various antenna design application

Machine learning and deep learning are showing wonderful results in various applications such as UAV, THz, textile, GPS, and Satellite. Its excellent capabilities for learning representations in real environments make it more suitable for applications. By using machine learning, the UAV is used for many civilian purposes and many other purposes. On the other hand, body-centric communication systems also use machine learning and deep learning to increase their capabilities. A review of recent reported uses and applications of machine learning and deep learning for various antennas has been performed in this paper.

Table 1. Beam selection alignment probability and achieved throughput ratio with different classifiers [7].

	P_A (%)	R_T (%)
Naïve-Bayes	59.31	91.14
AdaBoost	45.80	75.05
RBF-SVM	55.89	89.32
Gradient Boosting	69.05	96.49
Random forest	85.14	98.32

2.1. Machine learning and deep learning for millimeter wave for antenna design applications

The 30–300 GHz frequency band or the 1 cm to 1 mm wavelength range is the millimeter wave (mmWave) region of the electromagnetic spectrum. For the design of data transmission and sensing systems, the use of this millimeter wave frequency has many advantages. Machine learning and deep learning for millimeter wave applications have been described for different applications. mmWave technology is used in various types of fields. It has huge unlicensed bandwidth and has great flexibility and capability. Many types of wireless applications use mmWave antennas, and by using machine learning algorithms with the system, it becomes more flexible. Machine learning tools are finding useful applications in both mm-wave and massive MIMO antenna design. The large antenna array designed for mm-wave systems is required for hybrid beam-forming.

2.1.1. Wireless systems hybrid beamforming algorithm using reinforcement learning

To maximize the mean data rate of a multi-antenna wireless system, hybrid beamforming was implemented in millimeter wave (mmWave) frequency bands. A Reinforcement Learning (RL) algorithm is also demonstrated to speed up the selection of spatial beams.

There are two parts to a hybrid beamforming architecture. One is the analog beamformer, and the other is the digital pre-coder. The pre-coding weights for the various frequency portions of the baseband signal and flexibility happen when the digital pre-coder connects parallel streams of input symbols to RF transmission chains. The analog beamformer connects the transmit antennas with the output of the RF blocks. For wideband RF signals, because of its analog characteristics, the beamformer applies the same phase shift to each antenna [2]. The hybrid beamforming scheme can be implemented in many ways and in [3, 4], and [5], those ways are reported. A hybrid beamforming algorithm, which is the focus of this section, can maximize the earnable sum data rate of a mmWave Massive MIMO system. The weights of the analog beamformer can only belong to a set of uniformly quantized phase shift values for this purpose, and it is done jointly by the digital pre-coder and the analog beamformer to be used in transmission [6]. It is assumed that for a particular analog beam former, a lower dimensional wireless channel can be gained. Using Singular Value Decomposition (SVD), a lower-dimensional wireless channel's capacity to transmit digital pre-coder can be derived. By using a brute force search for the given channel state, the analog beamformer can be gained. It is possible to achieve this by moderating the number of transmitted antennas and phase shift values of each antenna. Reinforcement Learning (RL)was used to speed up the selection of the analog beamformer in this section. RLis mentioned based on a Machine Learning (ML) algorithm. The ML algorithm has earned experience from previous work and, using that experience, this RL algorithm assesses the execution of the candidate solution in every case of the process. Brute force search and the mentioned RL algorithm show similar sum data rates. But for the RL algorithm, fewer iterations are required.

2.1.2. Millimeter wave vehicular beam training with situational awareness

In this study, a feasible machine learning framework with situational realization has been proposed. This study also proposed vehicle locations and sizes in the domain to estimate the most favorable beam pair indexes. Three different ways have been applied to with appropriate feature ordering in polar coordinates, in Cartesian coordinates, and in grids of occupancy. Based on the situational features to forecast the best beam pair index, various classification methods have been compared. The remarkable development of prediction accuracy has occurred because of model use of GPS inaccuracies, the frequency of vehicle location reporting location errors in realistic implementations, and connected vehicles' various penetration rates.

A wide evaluation has been introduced for the newly introduced beam selection path. In this study, importance was given to the alignment probability and achieved throughput matrices. The beam selection performance has been compared with various machine learning models. The prediction performance at various levels is then evaluated by varying the number of vehicles in the feature. Noisy features of some realistic issues are also discussed in the study. With no GPS error, a straightforward feature set is encoded in Cartesian coordinates. Table 1 shows the classifiers utilized in this investigation. From the table, it can be seen that the random forest got an 85.14% alignment probability, which is a better result than other classifiers. With the alignment probability, the earned throughput does not scale, and though Naïve Bayes or gradient boosting have less alignment probability than random forest, there is no main difference between their throughput. This happens because several beams of power are almost the same. The model is good enough to find good beams, though the accuracy is not 100%.

It is advantageous to sacrifice some optimality in order to achieve low overheads, and this is especially important for millimeter-wave vehicular systems. In the study, system performance is compared and evaluated at various levels of situational awareness.

2.1.3. Beam alignment in millimeter wave massive multiple input multiple output (MIMO)

To earn data transmission and directional beam alignment (BA), a massive multiple input multiple output (MIMO) antenna array can be utilized to reduce the high path loss of the mmWave signal. Being packed into small form factors can be done by large antenna arrays because the millimeter wavelength is short enough. Multiple users with multiple beams are all served by the base station (BS) in an mmWave multi-user multi-stream system. Beam training based on a theoretical code-book is generally utilized to align beams for various users. For instance, in [9], authors suggested a method named "adaptive compress sensing (ACS). In [10], there is a method that works faster than the ACS method, and that method is the hierarchical search (HS) method. In [11], to combine the benefits of the ACS and the HS, a multi-path decomposition and recovery (MDR) method has been proposed. Using a hierarchical codebook to generate beam training is not unimportant for aligning beams for a large number of users. Using a hierarchical codebook to generate beam training is not unimportant for aligning beams for a large number of users. For all users, the BS must position beams sequentially. Time is wasted when, for every layer of the hierarchical codebook, the optimal code word index is fed back. Sensors or radars might provide the BS with information about the user's location. In mmWave systems, those sensors and radars are used for beam alignment, and they will have greater hardware overhead. An alignment process with partial beams leveraging AMPBML has been proposed in this paper for the multi-user mmWave massive MIMO system. The NN for the AMPBML is trained offline using simulated environments according to the mmWave channel model. The NN is then launched live to estimate the beam distribution vector using incomplete beams. The beams for all users are then aligned at the same time using the obtained indices of the dominating entries of the beam distribution vector. In this study, beam alignment for all users at the same time has been done by a hierarchical codebook and remarkably saves the entire training time. In this study, there is no need for previous knowledge of user location details to train NN, and remarkably, the system overhead will be reduced. The AMPBML shows better results than existing methods in terms of spectral efficiency and total training time slots. The better results of AMPBML also include hierarchical search, multi-path recovery, multi-path decomposition, and adaptive compressed sensing.

2.1.4. Millimeter wave massive multiple input multiple output for hybrid precoding

For future communications, millimeter wave massive multiple input multiple output (MIMO) is a remarkable solution. In mmWave MIMO, to minimize the complexity of the hardware and energy spending related to components of mixed signal, digital pre-coding and hybrid analog are important methods. Present hybrid pre-coding schemes have high computational complexity and cannot use spatial information. In the proposed solution, every specification of the precoders to get the most effective use of a deep neural network, the decoder is treated as a mapping relation (DNN). In this study, hybrid precoding and a deep learning architecture that supports mmWave massive MIMO were applied. The importance of this study is that it can enhance the spectrum feasibility of mmWave massive MIMO and also minimize the bit error ratio (BER). For those above results, the required computational complexity becomes less, and hybrid pre-coding gives better performance than conventional schemes.

In [12], a framework for the mmWave MIMO system is being created by combining deep learning (DL) with hybrid pre-coding. Here, this model is viewed as a deep network and a black box (DNN) as an auto coder. In the black box, activation functions create corresponding mapping relations by optimizing multiple layers of the network. Through the training stage, DNN is able to lower the computational time. This happens when, through the training stage, DNN captures structural details of the hybrid pre-coding scheme.

The performance of the DNN-based mmWave massive MIMO method has been explored in [12] using numerical analysis. The DNN framework is a process and is built by Keras. Observing the models in [13], the channel model was created without loss of generality. The BER performance is compared with many standard methods. The BER was also analyzed using different batch sizes of the training dataset and learning rates. In the simulation, the network has been trained for about 45,000 iterations. To verify better results, the fully digital SVD-based pre-coding method, completely GMD-based pre-coding method, SVD-based hybrid pre-coding scheme, and the traditional schemes have failed to maintain performance against the deep learning-based method. The BER result is compared with several batch sizes so that the mmWave massive MIMO scheme's performance can be analyzed. Then, with various learning rates, the DNN based mmWave massive MIMO scheme analyzes the BER versus SVR. The spectrum feasibility result has been given in [12] for the completely digital GMD based pre-coding scheme, the SNR of the DNN-based hybrid pre-coding scheme, and the spatially sparse pre-coding method. As the SNR is enhanced in all the schemes, the spectrum feasibility also gets better. Exploration of the relationship between the iterations of the deep learning-based strategy analyzed with the analog pre-coding scheme and MSE. The above investigation was carried out to determine the stability and performance of the suggested hybrid pre-coding approach.

2.1.5. Hybrid precoding for wideband millimeter wave massive MIMO systems

Millimeter wave (mmWave) massive multiple input multiple output (MIMO) has been proposed as a viable solution for future Internet of Things (IoT) data rates. Hybrid precoding is a viable result for mmWave large MIMO systems without a notable sum rate loss to reduce the number of radio frequency (RF) chains. The current study is evaluated using an unrealistic narrowband mmWave channel basedon using hybrid precoding or, on the other hand, the high resolution (HR) phase shifters (PSs) with huge power waste on hybrid precoding. For practical frequency selective wideband mmWave large multiple input multiple output systems, an energy efficient hybrid pre-coding approach based on one bit PSs has been investigated. A cross-entropy optimization (CEO)

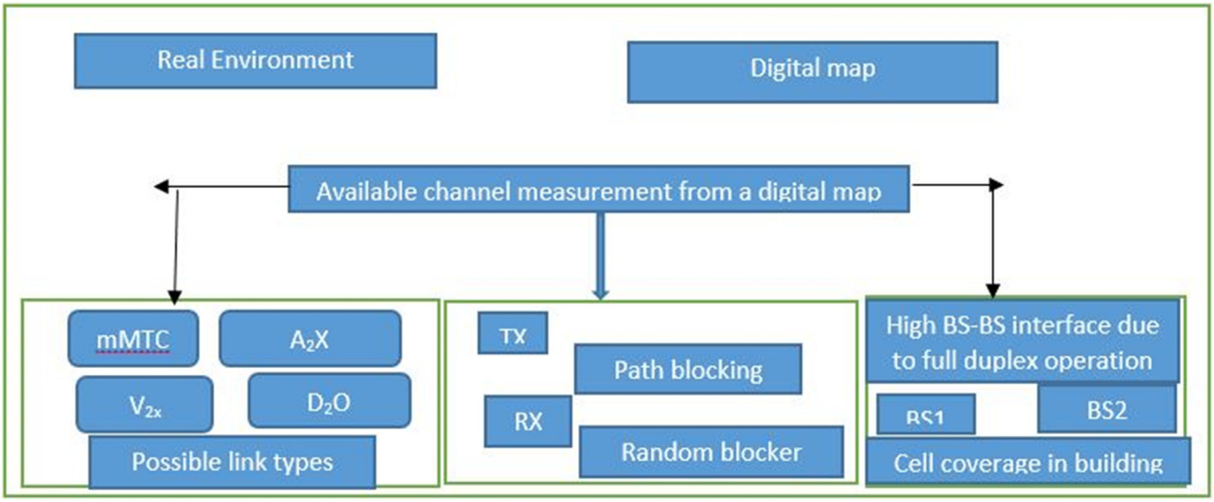


Figure 1. Map-based model with its characteristics [25].

based hybrid pre-coding strategy to optimize the earnable sum rate of the reviewed system has also been published as the CEO algorithm for machine learning breakthroughs. In the case of HR-PSs in general, the suggested CEO-dependent hybrid precoding plot from the event with one-bit PSs has been enlarged to show that the solution may be used in various plots. In terms of energy feasibility and near-optimal sum rate, the presented systems outperform some convocational methods.

The millimeter wave has unexplored and good spectrum resources. To fulfill the high data rate, the necessity for IoTmmWave is considered. Extreme propagation loss because of short wavelengths happens when high frequency mmWave signals are at 30–300 GHz, and this problem can be solved by high antenna array gain. The short wavelengths of mmWave communications are assigned high antenna array gain [15]. A new problem could arise from the use of a massive antenna array. In a sub-6 GHz MIMO system, for example, a dedicated radio frequency (RF) chain is typically required for each antenna to implement fully digital pre-coding [16]. For RF chains in mmWave, totally digital pre-coding is not sustainable [17]. A solution can be obtained from analog pre-coding with a RF chain, but it does not support multiplexing. Hybrid pre-coding has been suggested for multiplexing and sum rate of total digital pre-coding. A portable-sized digital pre-coder is enough to work out spatial multiplexing because of the low rank of mmWave channels. This hybrid pre-coding can get an almost optimal sum rate.

In this study, proposed solutions were compared with various solutions. In [14], energy feasibility and in terms of sum rate, CEO-based hybrid pre-coding has been explained. ACEO-based hybrid precoding with one bit PSs has been proposed for routinely selectable wideband mmWave large multiple input, multiple output systems. According to the results of the investigation, one bit PSs based hybrid pre-coding uses less power. Utilizing one-bit-PSs to experience array gain loss is done, and the result remains limited and constant. This answer proposes a CEO-based low complexity method to address the sum rate maximization problem. For the sum rate maximization problem, one bit PSs dependent hybrid precoding was built under practical control.

2.1.6. A generic deep learning dataset for massive MIMO antenna

The researchers presented the deep MIMO dataset, which is essential for any research. They provide a dataset of mm waves or a massive MIMO antenna design dataset. This is actually the generic dataset for mm wave-antennas. They also give detailed information about the structure of the generic dataset of the massive MIMO antenna. They provide some information about the channel's dataset design.

2.1.7. Multi-user hybrid beam-forming relyingon learning-aided link-adaptation

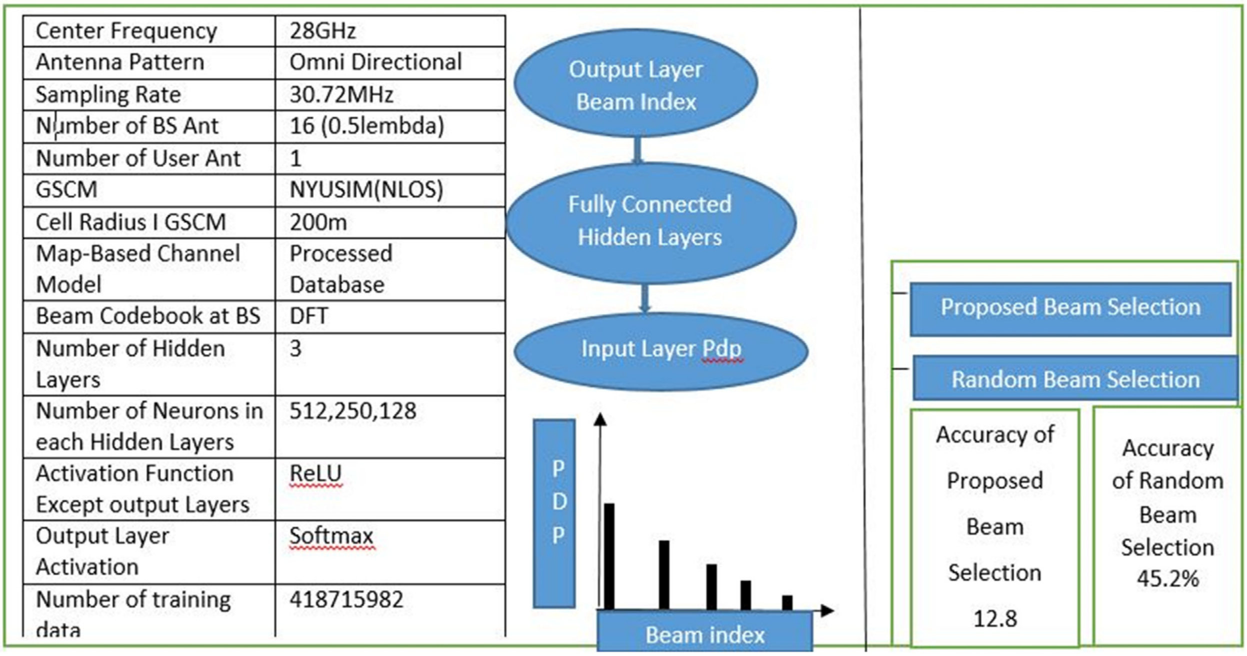
This study is based on a hybrid beam-forming architecture for multi-user mmWave systems' downlink, in which the number of antenna elements used at the base station to achieve beam-forming gains per user is proportional to the user's distance. The design is based on simulations that show that the proposed learning assisted in adapting the target bit error rate, resulting in a much higher data rate than traditional link-adaptation based on signal to noise ratio threshold values.

2.1.8. Learning beam codebooks with neural networks: towards environment-aware

In [20], a machine learning framework designed to learn environment-aware beam-forming codebooks for large-scale MIMO systems is presented. It is based on a neural network model that employs hardware limitations as well as learning beam codebooks from the environment and the user's location. This learning platform aids in the reduction of codebook size and can result in significant improvements over traditional codebook design.

In [20], the authors provide a hardware constraint on large-scale MIMO systems as well as an artificial neural network-based framework for learning environment-aware beam-forming codebooks. For the surroundings and user location, machine learning patterns have been used. Designing beam-forming codebooks has become an important research topic in academia and industry [21]. However, in large scale MIMO systems, the hardware limitations of mmWave/THz and the use of analog-only or hybrid transceiver architectures imposed new constraints on codebook design problems. This motivated the development of new beam-forming codebooks [22, 23], and [24]. In the system model, a millimeter wave BS (base station) equipped with M antennas can communicate with a single antenna user. In the machine learning approach, supervised learning is used. For the solution, there have been two communication scenarios. The first scenario is the Line of Sight (LOS) scenario, which is an outdoor scenario when users meeta LOS connection with BS. The other one is the None Line of Sight (NLOS) scenario, which is an indoor scenario and will happen when a user does not get a LOS connection.

In the end, the learned codebook in the LOS scenario with 64 beams hits about 90% of its upper bound, and with 128 beams, it reaches about 95% of its upper bound. It is very important in areas where analog phase shifters' resolution is limited. From the NLOS results, we can see that with 64 beams, learned codebooks reach about 90% of their upper bound.



Center Frequency	28GHz
Antenna Pattern	Omni Directional
Sampling Rate	30.72MHz
Number of BS Ant	16 (0.5lembda)
Number of User Ant	1
GSCM	NYUSIM(NLOS)
Cell Radius I GSCM	200m
Map-Based Channel Model	Processed Database
Beam Codebook at BS	DFT
Number of Hidden Layers	3
Number of Neurons in each Hidden Layers	512,250,128
Activation Function Except output Layers	ReLU
Output Layer Activation	Softmax
Number of training data	418715982

Figure 2. Performance evolution of map-based channels [25].

These results assure the similarity of the framework to learning beam codebooks that can optimize the size and beam patterns.

2.1.9. Map-based millimeter-wave channel models

In [25], an overview of millimeter wave channel models is offered, as well as the classification of map-based channels. Map-based models should be used in different modeling applications in the millimeter wave-range and they can be used as a supplement to SW test beds as they can support HW measurement.

Mobile broadband, mMTC (massive machine-type communication), and ultra-reliable low-latency communication are the technologies preferred for mobile broadband. Researchers have been debating potential frequency bands to serve such applications [26]. Map-based mm-wave design channel models that can utilize RT (Ray-tracing) have gathered momentum. It can also model irregular cell layouts and support new application link types such as D2D (device to device), V2X (vehicle to everything), and A2X (application to everything) (air to everything). RT is used to produce multipath channel parameters in map-based channel models (also known as site-specific propagation models) [27, 28]. Figure 1, shows the map-based model with its characteristics. It represents the area and scenario of selected applications and adopted technologies.

The database used contains a large number of snapshots for training sets used in machine learning methodologies [7, 28]. In the dataset, a DNN (deep neural network) based beam selection algorithm is used, which is a machine learning algorithm. Figure 2 shows that there is an overall performance evolution of map-based proposed models. In part 2, they used DNN-based beam selection algorithms and simulations of parameters. In the proposed algorithm, CDFs (Cumulative Distribution Functions) are used, and GSCM (Geometry-based Stochastic Channel Model) is used in the training sets and database.

Different models show different results. The beam selection algorithm has low accuracy, which is 12.8% using CDF, and the DNN-based beam algorithm using PDP (Power Day Profile) accuracy is 45.2%, which is more flexible. So, it will be very efficient.

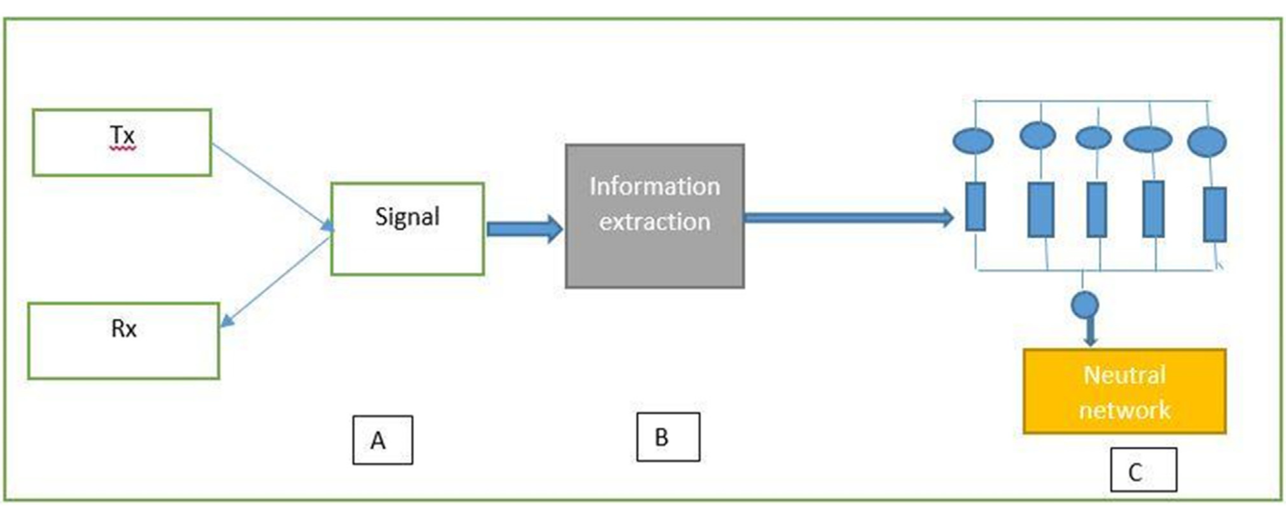


Figure 3. Three modules (signal transformation, information extraction, and the neural network)of the proposed model [102].

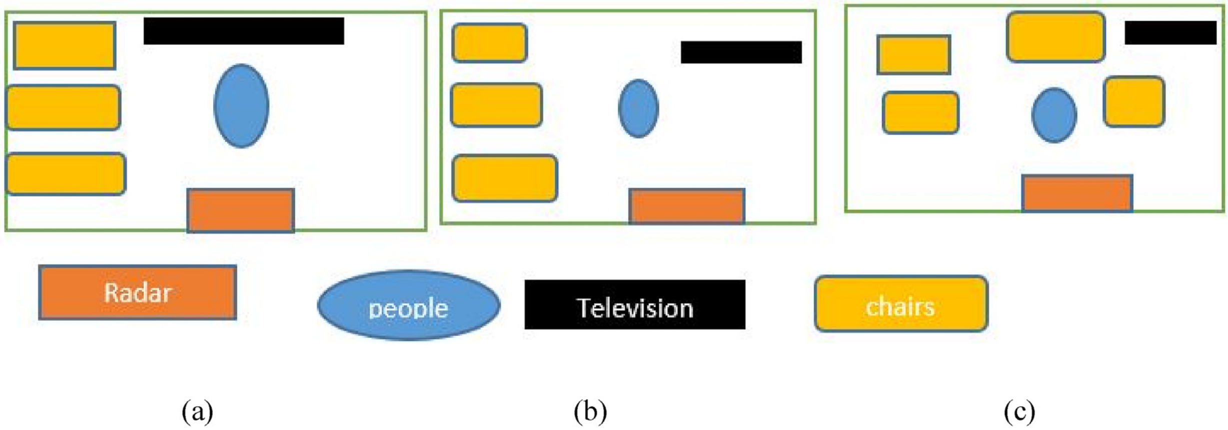


Figure 4. Three real test sceneries of the model [2]. (a) First Scenario, (b) Second Scenario, (c) Third Scenario.

Table 2. Accuracy result of three scenarios [102].

Types/accuracy	Knock	Left swipe	Right swipe	Rotate
Scene 1	48.33%	38.33%	51.67%	98.00%
Scene 2	35.00%	5.00%	23.33%	96.67%
Scene 3	38.33%	3.33%	30.00%	98.33%

2.1.10. Network analysis using millimeter-wave narrow-band energy traces

In [29], a model for evaluating a machine learning framework for performing protocol layer analysis and diagnosing physical layer faults in 60 GHz networks was provided. The major goal is to provide a machine learning framework that can appropriately classify transmitted networks and aid in the detection of network faults. The main focus of this type was on millimeter wave antennas and large bandwidth.

In essence, this model is a machine learning framework that uses template matching and EDHMM to infer protocol layer information automatically. The major aim was to determine the structural elements of the unpredictable behavior by analyzing the variability of channel traces. The challenge was solved using a directional antenna and a machine learning system.

2.1.11. Long-range gesture recognition using millimeter wave radar

A long-range gesture recognition model based on mm-wave radar is provided in this research. It is flexible in human-computer interaction (HCI).

Contactless gesture detection is a common way to achieve natural human-computer interaction (HCI) for a better experience, hence “in air” gestures will increasingly replace external physical gesture devices [30, 31]. Wireless communication has become the main focus of HCI. From all the other waves (sonic wave, WIFI signal, ultrasound wave), mm wave is the most suitable choice for this model. This design is based on a machine learning algorithm called CNN (Convolutional Neural Network). The first step is to create a long-range gesture detection model by extracting spatial-temporal aspects of the hand's reflection spots. After that, CNN is utilized to learn the attributes of the points for recognition. It can then recognize gestures automatically by using a millimeter wave radar sensor to implement the model. Figure 3 shows three modules of the proposed model. In Figure 3, they are signal transformation, information extraction, and the neural network. In hardware, Section MM Wave radar is used. In radar, the 3TX and 4RX antennas are used in sensing.

To verify the model, three real scenarios are used. For the test, some furniture was used in it. In the first scene, two participants stood 2.4 m away from the radar and were required to repeat each of four gestures for 30 min in order to collect 60 gesture data points. The first scenario is shown in Figure 4 (a). Then, in the 2nd and 3rd scenes, the two participants were at the same distance and just the placement of the chair and table was changed, as shown in Figure 4 (b-c).

From the output, the accuracy result was as in Table 2. The results of rotation scenarios are almost the same and have a high degree of accuracy.

The first three gestures' accuracy decreased greatly, and it is concluded that the external environment affects the model the most.

2.1.12. Large intelligent surfaces aided mm-wave massive MIMO systems by deep channel learning

In this paper, a deep learning strategy for channel estimation in large intelligent surfaces (LIS) with massive MIMO is proposed (multiple input multiple output). A twin convolutional neural network (CNN) architecture is created and maintained with the received pilot signals to estimate both direct and cascaded channels, and each user gets access to the CNN to estimate their own channel if there is a multi-user situation. With state-of-the-art deep learning based techniques, the performance of the proposed deep learning system is compared, and it shows better results. To obtain a vigorous estimation execution, several channel realizations are used to train the deep network. A separate set of test data is generated. Training data in the prediction stage, is used to confirm the performance. The existing DL based techniques [104, 105] are outperformed by the proposed deep learning framework and achieve reasonable channel evaluation accuracy. As a result, the suggested DL approach has demonstrated robust channel estimate performance, which is tolerant of changes in user positions of up to four degrees.

2.1.13. Deep learning based antenna selection for channel extrapolation in FDD massive MIMO

Massive multiple-input multiple-output (MIMO) systems include a large number of antennas, which makes obtaining accurate channel state information difficult, especially in the frequency division duplex mode. As demand for data transfer rates rises, massive multiple-input multiple-output (MIMO) systems have emerged as a crucial technology for the next generation of wireless communication [107]. Massive MIMO presents a significant issue for the base station (BS) in obtaining correct channel state information (CSI), particularly in frequency division duplex (FDD) mode [108]. For the FDD massive MIMO system, Yu et al. [109] designed an efficient downlink channel reconstruction approach. The distance between antenna elements in a massive MIMO system can be narrow enough that the channels have a significant correlation. The fundamental advantage of DL-based channel extrapolation is that it does not require an accurate model and may easily combine existing antenna selection approaches [110, 111, 112, 113]. As a result, proper DL-based antenna selection should be designed, as should effective downlink channel extrapolation from partial uplink channels. In this study, we used probabilistic sampling theory to characterize discrete antenna selection

Figure 5. Schematic diagram of THz TDS system [37].

as a continuous and differentiable function. For comparison, the performance of the DL and uniform antenna selection-based channel extrapolation is studied. Our proposed method outperformed the DL and uniform antenna selection-based schemes in simulations, and it was able to properly handle significant frequency gaps and uplink channel estimate inaccuracies.

2.1.14. 5G MIMO data for machine learning: application to beam-selection using deep learning

In [114], a specific dataset for investigating beam-selection techniques on vehicle-to-infrastructure using millimeter waves has been described. It presented a traffic simulator that combined a vehicle traffic simulator with a ray tracing simulator for generating channel realizations that are represented in the 5G scenario. It was designed to update the features of the traffic simulator. A specific dataset was used for investigating beam selection techniques. In this, many other modeling techniques using nyusim and quadriga [115, 116] were compared with RT. In this research, RT (Ray-tracing simulation) was used. RT can generate data for two key requirements. RT was convenient in this scenario, and different types of deep learning algorithms were used in the data processing. Among all of them, random forest and deep neural networks have given almost 60% accuracy. As the main focus was on mmWave MIMO, RSU antenna arrays were used for transmitting and receiving data. Future work on this paper is to make it more convenient and cost-effective.

2.2. Machine learning for body-centric communications

In the last few years, wearable body-centric communication systems have increased their applications and their areas. These systems are used in various applications like healthcare, sports, military, identification systems, smart phones etc. The applications are given below.

2.2.1. Body-centric for THz networks

THz communications are being celebrated as the key enablers for wireless communication systems. Recently, THz has been used so much in in-body and on-body communications. In this design, they actually talked about the THz band for body-centric communications and its technologies, channel, noise modeling, modulation schemes, and network topologies. From this paper you get some description of the THz sensing and imaging applications in the healthcare sector. It is very necessary to think about the RHz band to fight this pandemic. COVID-19 is impacting humans and the overall worldwide economy. Finally, the body-centric THz application design gives knowledge about using the THz band for in-body and on-body communications. In this paper they examine the THz band noise, modeling, modulation etc.

2.2.2. Human muscle mass measurement through passive flexible UWB-myogram antenna sensor to diagnose Sarcopenia

Human muscle mass measurements are a hot issue in the antenna area these days. As a result, the researchers discussed Sarcopenia in this design. The researchers demonstrate a non-invasive, passive flexible Ultra-Wide Band (UWB) myogram antenna sensor for predicting sarcopenia using human muscle mass assessment in this design. The result is a change in muscle fiber shape [60].

In this case, a non-invasive method for predicting sarcopenia by measuring skeletal muscle mass using passive flexible UWB-Myogram antenna sensor signals from various muscle locations was employed. Sarcopenia is diagnosed using a variety of diagnostic criteria, including quantitative and qualitative muscle mass measures. Furthermore, earlier detection of skeletal muscle mass measurement prevents metabolic side effects such as diabetes, depression, abnormal cholesterol levels, and weight gain. They use three ways to assess proteins, all of which are associated with using machine learning, such as linear regression for prediction data.

Sarcopenia is caused by a lack of skeletal muscle mass in humans. Dual energy X-ray absorption has recently been used to quantify skeletal muscle mass with some restrictions. The use of a passive flexible UWB-Myogram antenna to quantify skeletal muscle mass has been demonstrated. Sarcopenia can be predicted by measuring lean mass after fat signals have been separated from skeletal muscle mass using an NMF filter. For qualitative assessments, the proposed method eliminates the use of empirical calculations of lean mass. According to the prediction equation, a protein value of fewer than six indicates the presence of Sarcopenia, while a value of less than five indicates a severely affected person.

2.2.3. Privacy-preserving non-wearable occupancy monitoring system exploiting Wi-Fi imaging for next-generation body centric communication

The main focus of this application was on new, non-wearable, device-free, privacy-preserving wi-fi imaging-based occupancy detection systems for future smart buildings. Wireless and wearable gadgets are being developed to develop the next generation of communication networks. They discussed the detection of a person's existence during their daily activities without deploying on the person's body in this study.

2.2.4. Deep learning framework for subject-independent emotion detection using wireless signals

In this method, unique noise filtering techniques are used to gather most of the individuals' heartbeat and breathing signals from radio frequency reflections off the body. Deep learning approaches are also employed for comparing their findings. Their proposed wireless emotion detection gadget could also be used with ECG data in this paper.

2.2.5. Antennas and propagation for body-centric communications

Body-centric communication systems play an important role in the 4G generation of mobile communication systems. In this paper, authors provide details about the current position of body-centric communication systems.

Antennas for body-centric communications have been summarized well in recent publications [73, 74], including antennas for 10 MHz body surface communications [75] and button antennas [76, 77, 78]. Bandwidth is determined by the system or by spectrum allocations. It is very difficult to specify the radiation pattern requirements. The use of various sectors, like medical sensing and support, with either skin-mounted sensors or implants, is also getting attention. In this design, they

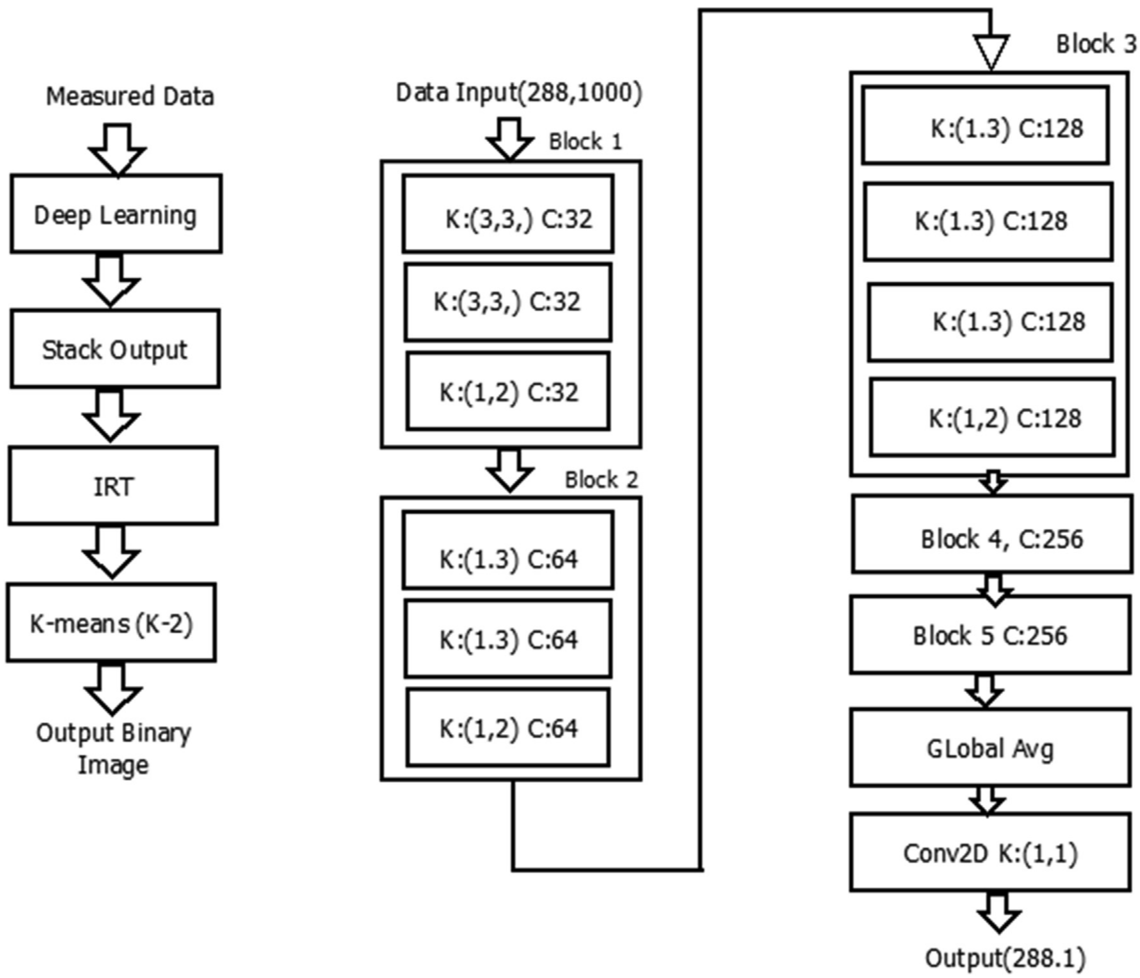


Figure 6. Schematic diagram of the THz DL CT model [37].

summarize the antennas and propagation for body-centric communication systems.

2.3. Machine learning for THZ communication system

The frequencies of THz are used for spectroscopy in different types of areas. The THz antenna can transmit and receive THz electromagnetic waves in the THz system as it has some features like wide frequency, small size bandwidth, and high rate. The THz frequency has significance in met material identification, the 6G network, visualizing hidden objects and beam selection. As we know, network systems are improving day by day, so 6G is the future network technology and is flexible. Met material and other hidden objects are important as we are not able to visualize some of the objects that are hidden. Beam selection is important as hybrid beamforming is very important for overcoming the attenuation that is created by the extremely high frequency in the THz band.

2.3.1. Terahertz deep learning computed tomography

A THz DL CT (Terahertz Deep Learning Computing Tomography) system that is capable of visualizing hidden objects with multiple-material systems is presented. Figure 5 shows the schematic diagram of the experimental setup, and Figure 6 is the schematic diagram of the THz DL CT model.

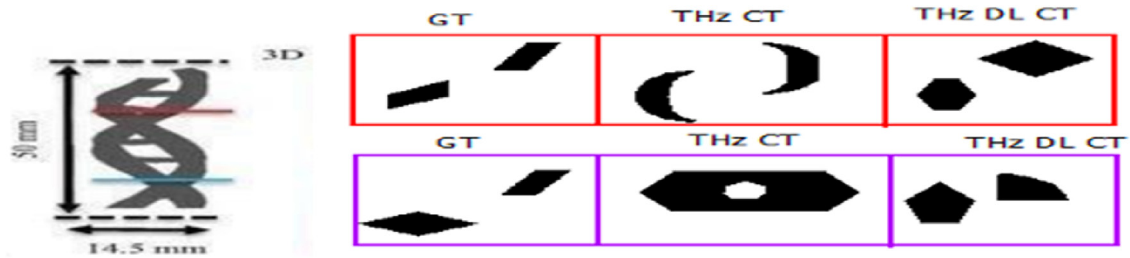
The final results of the comparison of THz CT and THz DL CT models. The THz DL CT model may use kernel filters to recreate superior images in the high spatial frequency area, which is useful for visualizing the interior structure of 3D objects. As previously stated, the MSE (mean square error) of the THz DL CT model was 1.86 percent, which is lower than the standard THz CT model. The final result, shown in Figure 7 (a-c), demonstrate that THz DL CT is a model capable of visualizing concealed objects using material systems.

2.3.2. Low complexity beam selection scheme for terahertz systems

When compared to some existing beam selection schemes, a proposed beam selection model that uses a machine learning algorithm that is an RFC (Random Forest Algorithm) based beam selection scheme is capable of providing a better arrangement between sum-rate and complexity by choosing the proper parameter settings. In this paper, it is considered that there is a THz multi-user uplink system featuring hybrid beamforming architecture on both the base station and user sides. The channel characteristics of L propagation pathways are assumed to be approximated and known on the base station side in this model, and the channel-related additional content is not taken into account. There is an exhaustive search approach for the maximum sum rate that can compute the sum rate under all beam combinations and locate the best transmitter and receiver pair. They also utilized the SVM model to see the results in this study, and after applying it, it was discovered that the SVM model causes data bias, which undermines the balance of two data sets. As a result, the RFC model's training set is similar to the SVM model's. This paper covered the communication problems and the machine learning approach that will help to improve the 5G communication system as well.

2.3.3. Secure deep learning for intelligent terahertz metamaterial identification

It's a system that uses the THz technology and the crypto-oriented CNN model to detect the presence of metamaterial in mixtures.



(a)

	MSE	SSIM	IOU
THz CT	0.03496	0.9325	0.3159
THz DL-CT	0.01864	0.9561	0.4601

(b)

(c)

Figure 7. (a) Comparison between THZ CT and THz DL- CT. (b) Numerical metrics on two algorithms, (c) Visible image and 3D THz images by THz DL-CT on a testing object [37].

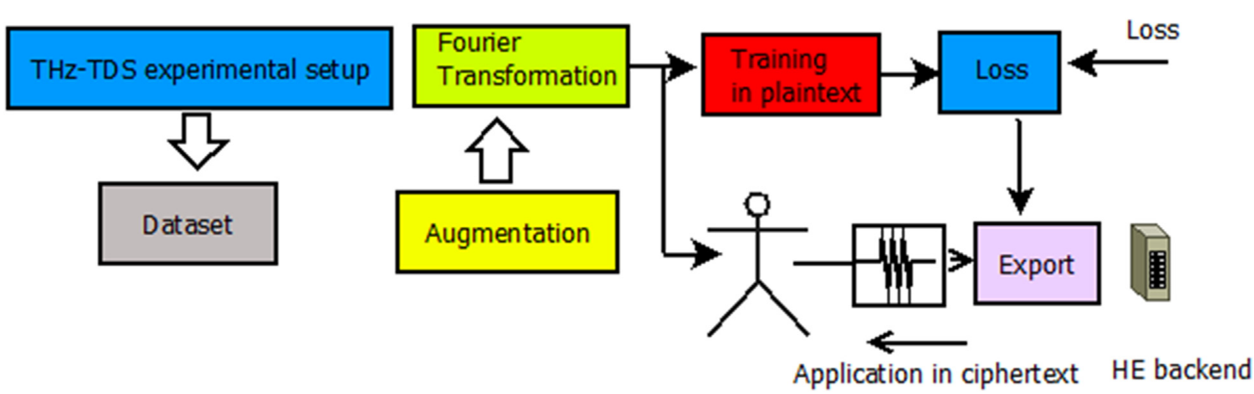


Figure 8. Workflow of private preserving THz metamaterial identification [39].

Figure 8 shows the workflow of private-preservation THz metamaterial identification. In the THz TDS (Time Domain Spectroscopy), a commercial photoconductive antenna is used to get electromagnetic response signals. The THz wave passes through the two lenses. To obtain huge amounts of data, random augmentation was employed in accordance with probable noise, and these augmented signals were translated to the frequency domain using a quick Fourier transformation. In the training step, CNN can learn to discriminate between features. After the network has been trained, it will be able to detect the presence of metamaterial. They encrypted the original data before passing it through the network and receiving all the results in ciphertext. This ciphertext can also be decrypted independently.

In the end, to compare the results, they used the SVM algorithm, the human baseline, and CNN. In the human baseline, the mean accuracy was 56.97%, the SVM method's accuracy was 87.9%, and CNN had 100% accuracy on every fold. These experiments were already done by SVM, but in this paper they proved that deep learning with CNN gives better accuracy in identifying the existence of metamaterials in mixtures.

2.3.4. 6G wireless communications: vision and potential techniques

It is a design of the potential requirements and an overview of 6G mobile networks. As we can see from 2G to 5G, the progress of mobile communication networks is centered on serving people. 5G technology allows for a latency time of 1 ms, and for that, 6G aims to make it less than 1 ms or nonexistent or undetectable latency. 6G is designed so that it can be more flexible than 3G to 5G. To increase data throughput, 6G will use a higher frequency spectrum than previous generations. It will outperform all other technologies in terms of latency and architectural adjustments. For THz communication, UM-MIMO and PM-MIMO techniques are used. In Figure 9, it is the design of 6G based on time-frequency-space resource utilization.

It will be possible to obtain it using machine learning approaches such as classification or neural networks, rather than any other calculation. As a big, data-driven network, 6G will be able to manage large amounts of data. Figure 10 has some promising features.

As given techniques, there are some power supply issues, network security issues, and hardware design issues. Millimeter waves and THz

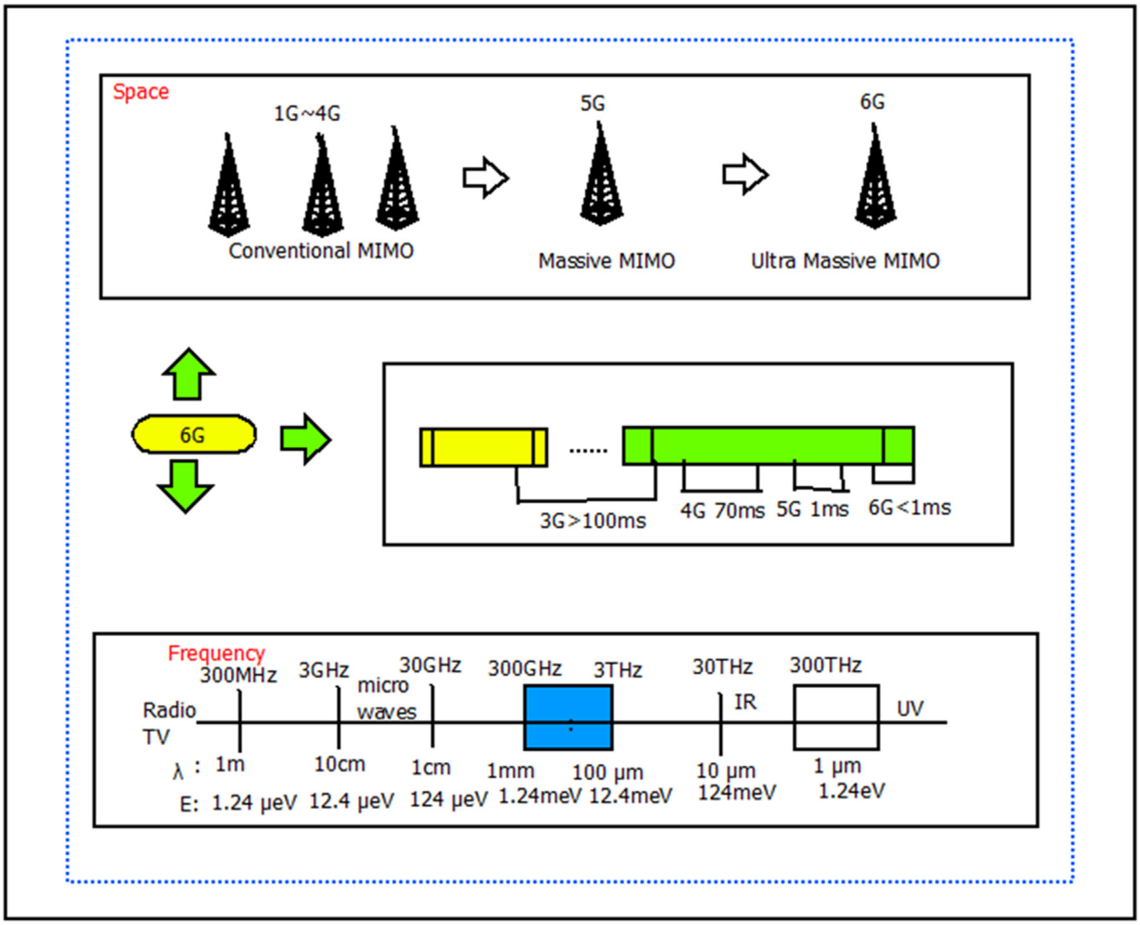


Figure 9. 6G based on the time-frequency-space resource utilization [40].

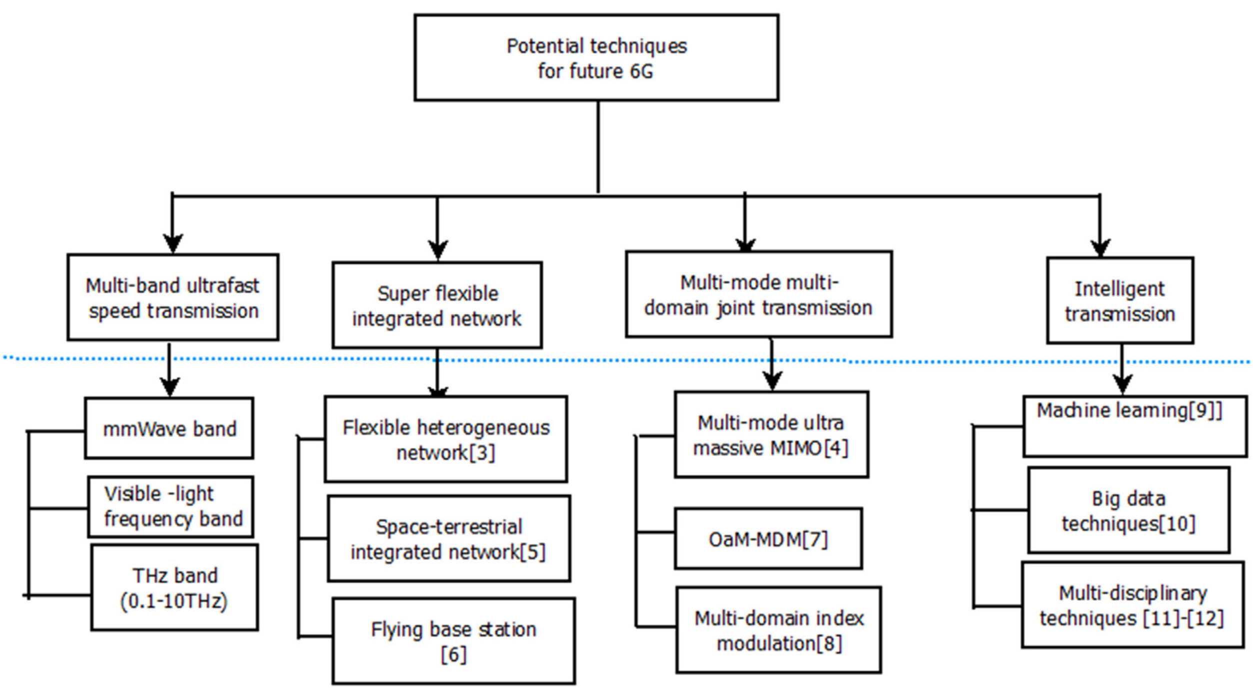


Figure 10. Some promising techniques of 6G network [40].

bands need to be recreated again for joint use. If the issues can be overcome, then it will be flexible.

2.3.5. Next generation terahertz communications: a rendezvous of sensing, imaging, and localization

It's a comprehensive and forward-thinking vision of THz communications that incorporates machine learning and THz antennas. As may be seen, the majority of current THz transceiver designs are electrical and photonic. While photonic technologies offer a data rate advantage, electronic platforms have a higher power generation capability (100 mW–1 mW compared to typical tens of microwatts in photonics) [42]. THz-band communication is trying to play a vital role in future 6G technology. THz communications, unlike mmWave communications, may take advantage of the enormous accessible bandwidths in the THz band to attain a terabit per second data rate without the use of any extra spectral efficiency augmentation techniques [43]. In this paper, we present some advanced technology areas that can be developed using THz technology. For example, in the areas of imaging, localization, and sensing. Previously, THz signals were used in imaging and sensing applications like food security, gas detection, and water dynamics. THz TDS is the most popular method for THz sensing [45]. THz can be easily used in imaging applications. The high gain of directional antennas allows for substantially higher spatial resolution (sub-millimeter spatial differentiation [44]) and targeted directed sensing and imaging. As future generations are expected to make wireless services location based, 6G networks that are based on mm-wave and THz frequencies are needed. For high-speed drone communications, THz bands like antennas are needed to detect location. Machine learning is needed for these services as the next generation is almost entirely based on artificial intelligence. Machine learning can handle large data sets. For instance, the THz-based localization system can locate any place. We need to use an antenna for collecting data, and machine learning will help with map interpolation. So, we can say that THz applications will be many in future communication systems.

2.4. Machine learning and deep learning for satellite antenna design application

A satellite is a spacecraft that travels around the planet in orbit. These satellites deliver signals to a central station, which develops programming for smaller stations that broadcast the signals locally through cables or the airwaves. For various applications, the use of machine learning and deep learning for satellites is explained below.

2.4.1. Acceleration of design and cross polar optimization for shaped beam reflect array antennas for space applications

A machine learning approach called Support Vector Machine (SVM) was used to develop and optimize reflectarray antennas in [46]. As a result, computing time is reduced without a decrease in accuracy. The main significance of [46] is that by using SVMs, crosspolar isolation and crosspolar discrimination can be improved, and the computing time remains the same.

As indicated in [46], artificial neural network (ANN), kriging, and support vector machines (SVM) algorithms can be used to develop surrogate models for the characterization of unit cells, so that the FW-LP (full-wave electromagnetic tool based on local periodicity) can be replaced. Then, based on a number of input parameters such as frequency, substrate, and geometrical characteristics, the FW-LP tool is used to create the unit cell pattern of electromagnetic behavior. A function was obtained from ANN or SVM and to train ANN or SVM those patterns were used. The function has a high degree of resemblance to training patterns and can predict unit cell patterns for fresh values. To characterize the whole matrix of reflection coefficients, SVMs are applied. ANN was utilized to determine the phase response of the reflectarray unit cell. In [46], it is stated that ANNs have recently been employed for the substrate, cross polarization for dual polarized unit cells, and phase shift to project the losses of the unit cell. Kriging has also been used to project the phase replay and associated losses. SVMs, Kriging, and ANN accelerated computation were used to analyze reflectarray antennas. An application used machine learning methods to create the design of reflectarray antennas. The analysis algorithm is called hundreds or even thousands of times to obtain the unit cell geometry that gives each reflectarray element the required phase shift. SVM is used in this case to make reflectarray design and to preserve efficiency of cresspolar and copolar manufacturing, as well as to significantly speed up operations. Many methodologies for training SVMs have been devised for the analysis of a large reflectarray for Direct Broadcast Satellite (DBS) applications, as detailed in [46]. The design process is detailed and carried out using a Method of Moments based on Local Periodicity to gain access to accuracy and computation time acceleration (MoM-LP). ML algorithms are a hopeful system to speed up reflectarray study.

2.4.2. Beam hopping in multibeam satellite system

A Deep Learning (DL) based path has been developed to simplify feasible beam hopping (BH) in multibeam satellite systems. In the satellite coverage area, to manage time variants and irregular traffic requests, BH can maintain flexibility. A learning and optimization approach was used to create a rapid, near-optimal, and viable solution for BH scheduling. In [47], it is mentioned that getting optimal performance within a reasonable time is not possible for traditional frequent optimization paths and data-driven techniques. Many studies suggest that the path taken in [47] can improve the solution's performance and capability by using the optimization component, while the learning component can speed up the process of BH pattern selection and allocation.

The fundamental purpose of this work is to ensure that satellite resource distribution in multibeam system situations with non-uniform traffic needs is optimized by utilizing data-driven pathways. In [48], it is mentioned that for future broadband multibeam satellites, it is important to have the ability to control the system resources over the service coverage area. The demand for some spot beams in large multibeam satellites surpasses the limit and they are known as hot spots. On the other hand, the demand for some spot beams is less than the service they can provide, known as cold spots. So this causes a problem because where demand is high, capacity is low, and where capacity is high, demand is low as well. Because the resources per beam are set and consistently distributed throughout beams, standard payloads provide the same capacity for each beam. But in this solution with flexibility, the system capacity can be maximized for allocation in different areas where needed. In many ways, the satellite's payload flexibility can be ensured by the distribution of power, time, and bandwidth. In [47], it is mentioned that in the satellite coverage area, a high level of flexibility to maintain time variants and irregular traffic requests can be provided by the Beam Hopping (BH) system. For some period of time, all the satellite resources can be focused on providing service to a selected subset of beams with BH until the demand is met. Depending on a space time-dispatch pattern, in every time slot, the group of illuminated beams swaps and it is replayed from time to time. In [49], an iterative algorithm for BH illumination design has been proposed. On the other hand, in [50], BH for power minimization has been proposed, so it is clear that different works show the beam illumination pattern design in different ways. Gaining feasible BH patterns while search space expands more rapidly is hard for pattern design inBH. A satellite system requires a long computation time to render a complex optimization process because it is composed of hundreds or thousands of beams. To get a better solution, the complexity of BH design is expected. In wireless networks, complex resource management can be done by creating efficient algorithms with DL. In [47], researchers looked into the role of DL in BH optimization [47]. A better methodology to combine learning and optimization methods for BH has been presented to overcome the shortcomings of conventional algorithms and classical learning models. The number of elements in the beam patterns for BH gives the top forecast precision in deep learning. The combination of optimization components and DL can be done simply by

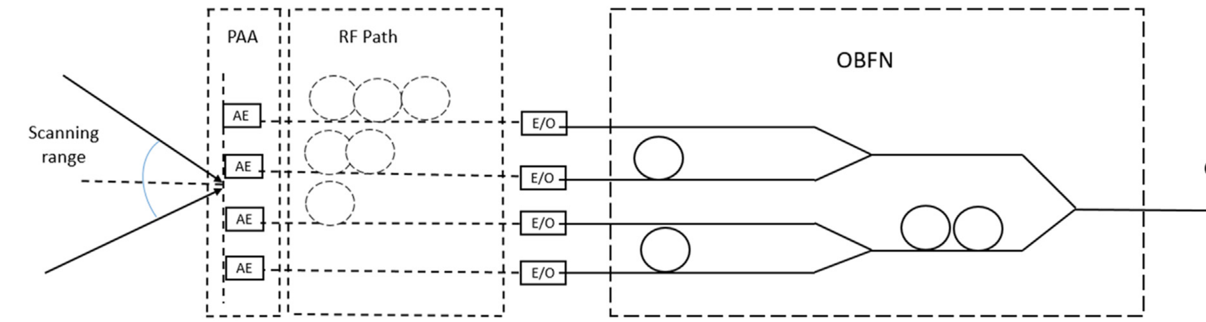


Figure 11. Antenna elements (AEs), a phased array antenna (PAA) system, and an optical beamforming network (OBFN) are all examples of optical beamforming networks [52].

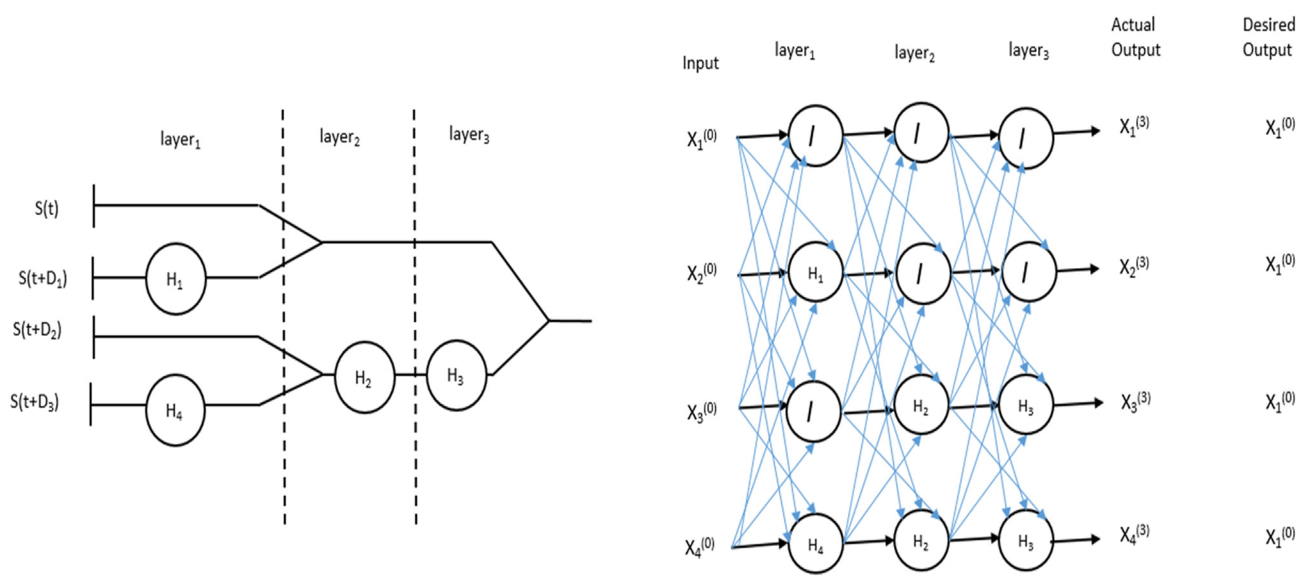


Figure 12. The right diagram is its neural network configuration and in the left there is OBFN system (4 × 1) [52].

the proposed algorithm. In [47], using computational time and optimality, an analogy has been made between the proposed DL-based optimization algorithm (DBO), optimal and suboptimal paths. This solution shows better BH pattern selection, feasibility, and enhancement in performance.

2.4.3. Tuning optical beamforming networks

A deep neural network representation of adjusting Optical Beamforming Networks (OBFNs) was developed in this part. To get signals from particular projections, phased array antennas (PAAs) are level and small, requiring OBFNs to be tuned so that communication between satellites and plains can be done. This topic is important because tuning large scale OBFNs for any delays can be done with the help of deep neural networks.

The planes should focus their transmission beams in the direction of the satellite so that they can receive or transmit Radio Frequency (RF) signals to or from the satellite. Antennas with omnidirectional are not good for low gain. In [53, 54], it is mentioned that steering dish antennas mechanically is the usual solution. This solution has drawbacks like increased drag force, high maintenance costs, and a large dimension. In [55, 56], it is mentioned that because of low maintenance costs, agility, and reduced drag forces, the potential solution is the Phased Array Antenna (PAA) system. A PAA system is developed using a beamforming network and an array of antenna elements (AEs), as shown in Figure 11. From a specific angle, a time-delayed version of the aimed signal is received by every AE. With predetermined delay values, the received signal will be delayed while it goes through RF paths. In [53], for simplification of the tuning process to the bottommost path, the signal arrives first. As it is discussed [57], the delay points are tuned, so that the aimed delays can be matched while the signal passes with the help of a beamforming network. In [57] mentioned, the delay points are tuned, so that the aimed delays can be matched while the signal passes with the help of a beamforming network. According to [58], the aimed signal adds up in phase using a delay and a combination characteristic of the beamforming network. The intended signal and its time-delayed form are well defined in [52]. An optical beamforming network was employed in [59, 60], and [61] with optical ring resonators (ORRs) as configurable delays. The ORRs genetic method [64] and nonlinear programming optimization [62, 63] were employed to find the optimum parameter.

The OBFN structure is designed to cover a wide bandwidth while maintaining low cost, scalability, and a low number of ORRs. For the same bandwidth and antenna specifications, Nugroho et al. [53] discovered that the asymmetrical binary tree-structured OBFNs and their neural network representations as shown in Figure 12 are scalable and have the least amount of ORR.

Figure 12 shows the diagram of the neural network configuration, and on the left there is the OBFN system (4 × 1). From training examples of a neural network, we can obtain input vectors and their corresponding aimed output. The signal received by each antenna element is the neural network's input in Figure 12. The aimed output is acquired via the reference path, and this is the signal.

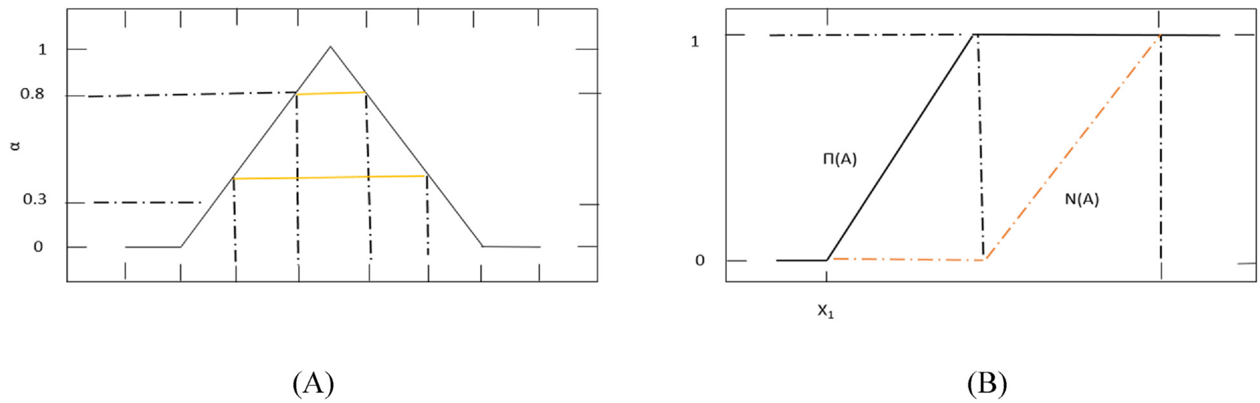


Figure 13. (A) A triangular PD, π(x), and (B) the corresponding possibility Π (solid) and necessity N (dashed) measures [78].

To take advantage of OBFN, a deep learning algorithm is suggested so that the OBFN system can be tuned in a big way. The unique structure of OBFNs can be viewed using a deep neural network. A deep learning algorithm works for a specific OBFN structure to find ideal ORRs parameters for 4×1, 8×1, or 16×1 OBFN. Utilization of quantifiable signals by deep learning methods can be done as a preparation paradigm since it has data-driven skills. For future development, it is important for online tuning to use real data as a measurable signal, as used in [52].

2.4.4. Mobile tracking and antenna pointing in satellite terrestrial network

Growing mobile services have been unable to provide facilitation for conventional satellite terrestrial networks in recent years. Reduction of the communication load by processing collected data through accurate mobile terminal location is the main problem mentioned in [65]. An artificial intelligence (AI) based pointing and tracking method for mobile terminals and stations in satellite terrestrial networks has been developed to ensure that mobile stations and terminals experience minimal communication interference and can access ideal antenna signals from other stations or terminals. An AI-based self-learning (ASL) network framework has been designed for data sampling and filtering in this solution. The framework also supports unsupervised satellite selection, antenna adjustment schemes, and mobile terminal and station tracking by mobiles.

With the rise of mobile services supported by satellite terrestrial networks, both data analysis and data transmission need greater time and resources [66, 67]. In [68, 69], it is mentioned that the distribution of high-quality service on satellite terrestrial networks has become more difficult. Conventional satellite terrestrial network service quality has been declining because of the increased number of devices and mobile stations. It is quite difficult to communicate with several mobile devices quickly over a standard satellite terrestrial network. Mobile device movement pathways, on the other hand, are quite complicated. For terminals and stations, mobile pointing, tracking, and data analysis based on AI are very important.

While talking among satellites, we must follow and precisely point the mobile target for ground stations and terminals in satellite terrestrial networks. To get ideal signal reception requirements, stations or terminals require changing the pointing of satellite antennas on time while relative movement happens between satellites. Because of high turbulence in the mobile carrier for mobile services in the satellite terrestrial network, the elevation of the ground mobile station and terminal, as well as the antenna azimuth, will change rapidly. By aiming antenna beams at compatible satellites, we can increase communication. Artificial intelligence is used to evaluate the quality of mobile communication on satellite terrestrial networks, engage with mobile targets, and explore a new road to integrative collaboration. Multi-mode perception information must be considered when using different types of sensors to detect information about moving things. Then pointing and tracking were introduced to mobile phones. In [70], it is mentioned that to get data from various sources and then learn to schedule tasks, optimize allocation of resources, and train needs unsupervised learning with satellite terrestrial networks.

2.4.5. Satellite communication

In the satellite communication (SatCom) system, the use of artificial intelligence (AI) mechanisms was explored in this study. Conventional SatCom is dependent and controlled totally by human intervention. The AI equipment can do SatCom related work and can deal with those challenges. In the SatCom field, long-term AI -related development has been discussed.

A reduced client standard and high operational expenditure (OPEX) have been encountered because satellite operators' teleports need human involvement. Satellites are built to reconfigure their communication budget on a millisecond basis with the imminent placement of a flexible payload. To maintain the client's service level covenant, short design time, response time, frequency, power, and beamforming are needed for radio resource management algorithms. By adding the requirement to coordinate space networks of hundreds or thousands of satellites, the emergence of satellite mega constellations only creates problems. Soon, everyday satellite operations are expected to include automation algorithms. Deep learning has the ability to simulate any nonlinear function, and it will play a prime role. AI may have an impact on flexible payload optimization, beam congestion prediction, interface detection and classification, and anomaly detection in telemetry data.

2.5. Machine learning for unmanned aerial vehicle

Wireless communication networks will rely heavily on unmanned aerial vehicles (UAVs). When compared to older ground-based technologies, their acceptance in various communication-based applications is predicted to improve coverage and spectral efficiency. This new strategy, on the other hand, will introduce fresh changes to the network's communication mechanisms. In this case, the machine-learning structure should be able to solve the different issues that have already been recognized when UAVs are used for communication. A comprehensive review is presented, including all relevant research papers in which machine learning approaches have been applied to UAV-based communications to improve different design and functional elements such as channel modeling, resource management, and security.

2.5.1. UAV in the machine learning environment

For academic and industrial research, unmanned aerial vehicles and machine learning are key applications. This paper's main focus is on applying machine learning and its techniques to many fields. This is a very useful application for UAVs, which are used in the environment. The unmanned aerial vehicle (UAV) and machine learning are two of the most important aspects of the fourth industrial revolution. This was actually created to research the importance of machine learning and the scope of use for the UAV. The UAV was actually used because of its low altitude, high resolution, flying capability, and probability. In this application, they focus on the implementation of the UAV environment. Finally, they proved that the UAV and machine learning both have a huge scope for scientific research.

2.5.2. UAV based 5G radio access networks

The authors explain why, how, and which sorts of machine learning approaches are effective for constructing UAV-based radio access networks in this application. They concentrated on supervised and reinforced learning systems in particular. They also discussed radio access networks and compared them to radio access networks based on unmanned aerial vehicles.

2.5.3. Construction resource localization based on UAV-RFID platform

They discuss data collection via a UAV-RFID integrated platform and data analysis utilizing the k-nearest neighbors machine learning technique in this UAV application. This paper characterizes localization as a classification problem by discretizing the location regions and applying a machine learning technique to solve the problem. They discuss data collection via a UAV-RFID integrated platform and data analysis utilizing the k-nearest neighbors machine learning technique in this UAV application. This paper characterizes localization as a classification problem by discretizing the location regions and applying a machine learning technique to solve the problem. Preliminary tests show that using the UAV-RFID platform to locate construction materials is a viable option.

Understanding the context of building sites necessitates having location data for construction resources. To obtain location data, most sites still rely on human observations. Technology and research, on the other hand, have limitations when it comes to locating construction resources, as most of them have a restricted recognition range and accuracy for outside building sites. By combining UAV with RFID platforms, the limiting identification range of RFID might have been overcome due to the higher agility of UAV. Preliminary tests show that using the UAV-RFID platform to locate construction materials is a viable option.

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2.5.4. Artificial intelligent for UAV enabled wireless networks

The authors provide a detailed summary of current research in the area of artificial intelligence-enabled UAV networks in this article. They also go through some of the current research's limitations and present some prospective concepts that could be pursued in the near future. They also report on some of the work done in Florida for UAV-based networks in order to examine the deployment of intelligence at the boundary of UAV networks. Furthermore, they provide a thorough introduction to each artificial intelligence topic covered in this work, allowing readers from a variety of backgrounds to comprehend it.

Smart cities and aerial base station deployment are two examples of UAV applications that provide motivation. The researchers looked at how machine learning techniques are utilized to improve the performance of UAV networks in these applications. They also provide some insight into how FL techniques are applied to UAV networks.

2.5.5. Predicting within-field variability in grain yield and protein content of winter wheat using UAV-based multispectral imagery and machine learning approaches

Crop yield and quality forecasting are essential for profitable agriculture. Commercialization has resulted in low-cost multispectral cameras being attached to UAVs, and the development of machine learning algorithms has made the prediction process more valuable. Machine learning is used to forecast wheat grain production and protein content by using spectral reflectance and plant height. In this research, they compared the performance of machine learning based on reflectance and classic linear regression models for forecasting wheat grain yield and protein content.

2.5.6. Cattle detection and counting in UAV images based on convolutional neural networks

The authors proposed using UAV photos to detect and count cattle in this investigation. The targets all look to be almost the same size, which is a peculiarity of UAV photos. Furthermore, introducing the concept of domain adaptation could help improve the performance of a slightly different dataset. Other slow-moving animals can also be detected and counted using cattle detection and counting devices.

2.6. Machine learning for textile communication systems

These antennas are designed with textile materials. These antennas are important for developing wireless electronic textiles. It helps communicate between garments and sensors with external devices. Wearable antennas are flexible, and washable, and the following papers are focused on these. Sensors and techniques are used to make the textile system more flexible.

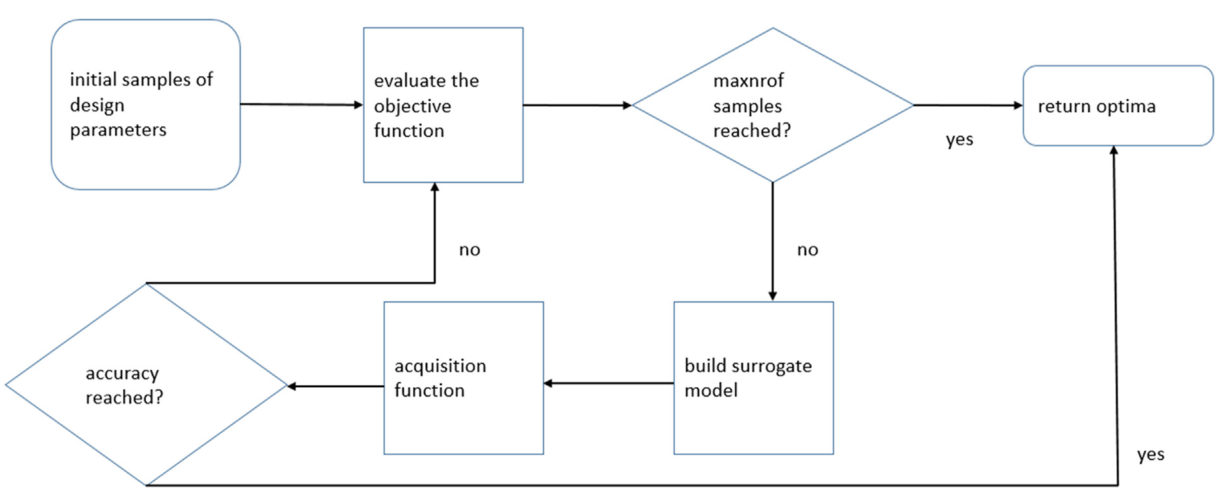

Figure 14. Flowchart of BO algorithm [78].

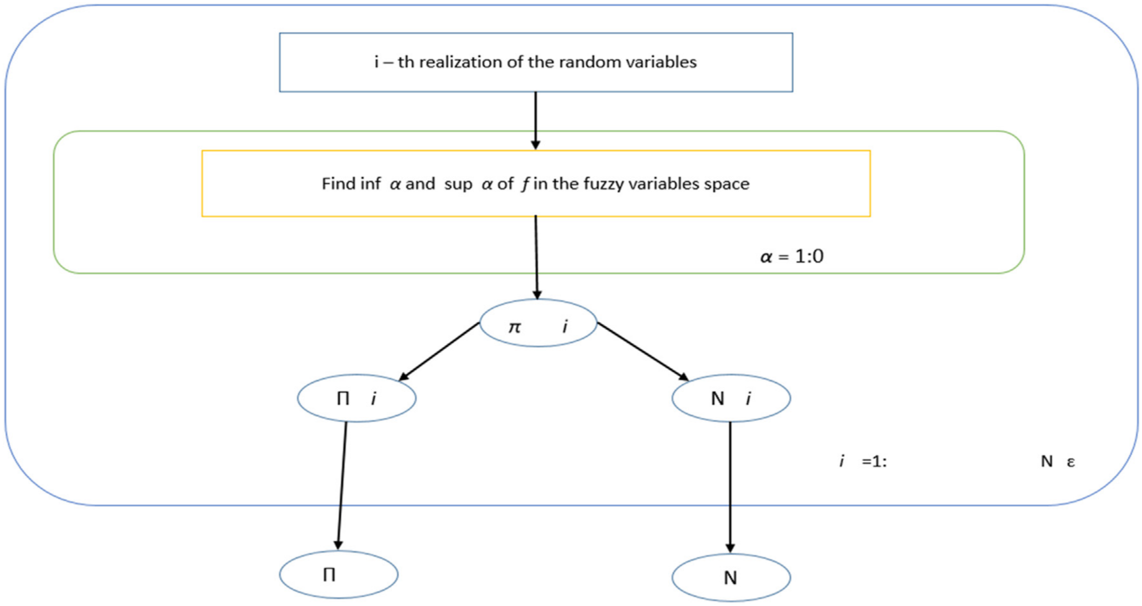

Figure 15. Proposed hybrid algorithm [78].

2.6.1. Machine learning-based hybrid random-fuzzy modeling framework for antenna design

It's a mixed-machine learning approach for propagating aleatory and epistemic uncertainties in antenna design. UQ (uncertainty quantification) for antenna design follows statistical methods, and there are some complex scenarios to design with that. In textiles, the UQ approach is followed [79]. As it uses statistics, they use probability distribution functions with some random variables, and, because of that, some represent variables affected by epistemic uncertainty. In this paradigm, x is a real-valued parameter represented by a PD (Possible Distribution) (x), such that:

π: R $\rightarrow$ [0,1],$\exists$ x $\in$ R: π (x) = 1.

In this case, PDF represents the frequency of an event over a given time interval, and PD represents the value that x is presumed to be. And 0 denotes an impossibility, whereas 1 denotes a possibility. As shown in Figure 13, PD can be specified as rectangular or triangular. PDs are commonly used to represent so-called total ignorance, which occurs when no information about a parameter's variability is known [80]. The epistemic variable in fuzzy sets is x. It is distinguished by its cuts. Cuts are indicated by red lines in Figure 13.

Due to various constraints, a machine learning strategy combining BO (Bayesian Optimization) and the PC expansion method has been developed. Figure 14 BO is mainly used for global optimization problems. Figure 15 is the proposed hybrid algorithm which is combined with BO and PC.

The proposed algorithm speeds up the standard of hybrid algorithms as it uses the BO framework. The final hybrid UQ method presents better accuracy and higher computational efficiency.

2.6.2. On the use of knitted antennas and inductively coupled RFID tags for wearable applications

A knitted folded dipole antenna with an inductively connected RFID chip was designed and tested. Wireless smart gadgets are now employed in clothing. Physiological sensors and low-power computing units are integrated into these garments, enabling continuous biomedical monitoring and activity tracking [82, 83]. RFID (radio--frequency identification) technology uses low-power radio waves to collect data and automatically identify items. It has been demonstrated that the backscattered power (RSSI) transmitted by a passive RFID tag may be employed as a metric for identifying material deformations for typical metal-based tags [84]. They used knitted-based manufacturing techniques to create comfortable and battery-free wearable stain sensors, just as they did in this work. Comfortable to wear, very stretchy, with impedance matching between chip and antenna, and appropriate radiating properties to continue communication at various levels of physical deformation, are all requirements for this sensor. A wearable stain sensor is paired with a folded dipole antenna in this device. SVM and Gaussian filters are two machine learning techniques that are used to evaluate data. The goal of this system was to track the movements of the body, hence knitted antennae implanted in the host garment with inductively connected RFID tags were constructed.

2.6.3. ClothFace: a batteryless RFID-Based textile platform for handwriting recognition

It's a ClothFace technology prototype based on UHF-RFID for handwriting recognition embedded in cotton fabric. Textile antennas and a 10 × 10 array of RFID ICs (integrated circuits) with a unique code were employed in this. Human-machine interaction is always reliant on touch or body movement, and the most prevalent on-body interfaces, such as trackpads and tapping buttons [86, 87, 88, 89], are typically blended around the arm to identify hand movement. Skin electronics [90] have recently been proposed as a flexible technology for on-body touch and gesture recognition. This project is an expanded version of [91], which showed a basic prototype of ClothFace technology, a battery-free textile-based handwriting platform. The upgraded work will be a real-time recognition system that will be tested in real-world scenarios. It can recognize any number from 0 to 9 and can also handle complex functions thanks to machine learning methods. The test error rates ranged from 0.23 to 1.7 for picture identification using a machine learning technology called CNN (Convolutional Neural Network). This technology will enable us to turn the clothing and textiles we wear on a daily basis into sophisticated user interfaces. It can help the user increase their character recognition accuracy.

2.6.4. Surrogate-based infill optimization applied to electromagnetic problems

An overview of SBO (Surrogate Based Optimization) methods is presented. Mostly, this paper focused on data-driven approximation using several SBO methods. There are many types of surrogate models, like SVM and Gaussian Process (GP). Basically, SBO creates a mapping

Table 3. Comparison of the different machine learning techniques used in the investigated papers for Millimeter Wave.

Reference No.	Antenna Used	Algorithm Used	Comparison to	Result
[1]	MIMO antenna	Reinforcement Learning (RL) algorithm	Brute-force search	Reduction in the number of iterations required to locate the most suitable analog beamformers and digital precoders for transmission, without compromising the upper bound data rate reached through brute-force search.
[7]	Millimeter wave antenna	Random forest	Naive-Bayes, AdaBoost, RBF-SVM and Gradient Boosting	The results suggest that given perfect assumptions, we may get up to 86 percent alignment probability.
[8]	MIMO antenna	Alignment Method with Partial Beams using ML (AMPBML)	Multi-path decomposition and recovery, as well as adaptive compressed sensing and hierarchical search.	In terms of total training time slots and spectral efficiency, the AMPBML outperforms existing methods such as adaptive compressed sensing, hierarchical search, and multi-path decomposition and recovery.
[12]	MIMO antenna	Deep learning based hybrid precoding method	Hybrid precoding schemes	The result is minimization of the bit error ratio and enhanced spectrum feasibility of the mmWave massive MIMO with low computational complexity.
[18]	MIMO antenna	ray-tracing data		The dataset can be used in deep learning applications.
[19]	hybrid beamforming	KNN	deep learning	Learning assisted adoption gives a higher data rate than the conventional link data rate.
[20]	M antenna	LOS		Developed a machine learning-based framework for learning the surroundings and beamforming codebooks that are hardware responsive.
[25]	Large array antenna	beam selection		Map- based millimeter Wave channel model
[29]	Misaligned antennas	EM		Developing channel traces
[102]	Antenna (3TX,4RX)	R-D,FFT		mmWave sensing is used to create a long-range gesture recognition model.
[103]	MIMO antenna	Deep Learning	state-of-the-art DL based techniques	The existing DL based techniques [104, 105] are outperformed by the proposed deep learning framework and achieve reasonable channel evaluation accuracy.
[106]	MIMO antenna	Deep Learning and Problemistic sampling framework	ULA	The Massive MIMO channel extrapolation algorithm is effective.
[114]	RSU	Random forest, deep neural network	SVM, decision tree, AdaBoost	The result gives about 63% accuracy, and it is a very convenient technique.

between input and output parameters. It speeds up other optimization algorithms. Textile antennas are made of a nonconductive textile substrate. To tackle the inverse problem of textile antennas, the SUMO (Surrogate modelling) toolkit is employed. SBO is a toolkit that is based on the EI (Expected Improvement) criterion and is incorporated into the SUMO toolbox. To overcome the EM problem, they employed a machine learning approach called SVM. SVM aids in the reduction of errors between measured and simulated data.

2.7. Machine learning and deep learning for global positioning system antenna design application

In order to get an accurate determination of geographical locations, the Global Positioning System (GPS) has been developed for civil and military use. Transmission of information by using satellites in Earth orbit allows us to measure the distance between the user and the satellite. For many applications, the use of machine learning and deep learning for GPS has been described below.

2.7.1. In multipath environments a machine learning approach for GPS code phase estimation

A neural network (NN) dependent delay locked loop (DLL) is built into Global Positioning System (GPS) receivers for multipath reduction in [93]. The NN works on samples that are evenly spaced in the autocorrelation function. A statistical distribution model takes into account multipath time delay and power attenuation, and the NN is trained using that model. Three additional solutions are compared to the recommended solution. In high multipath situations, the NN based DLL produces less code phase root mean squared errors than the three standard models.

Multipath interference in the Global Positioning System (GPS) has been recognized as one of the critical error drivers. Multipath signals alter autocorrelation functions in the phase locked loops (PLLs) and delay locked loops (DLLs) of GPS receivers. This causes carrier phase estimates and biases in the code and leads to errors in the navigation solution. Many techniques have been developed to mitigate the effects of multipath. They are grouped into two categories: one is signal processing techniques, and the other is antenna techniques. The conventional early-to-late (E-L) DLL was unable to handle the aforementioned scenarios. They do not make use of multipath signal statistical models and are still sensitive to multipath effects. A NN-based DLL (NNDLL) was created in [93] to alleviate positioning issues caused by multipath by focusing on the autocorrelation function in the receiver's evaluation. It provides more information about multipath signals than a pseudo range measurement. As a result, the proposed method differs from other machine learning-based multipath mitigations. The NN's goal was to determine the receiver's motion and the type of multipath environment in order to adapt the receiver's tracking strategy. In [94], NN is in charge of sample processing for the autocorrelation function. This technique uses samples from the autocorrelation function to create an estimate of the code phase error. This occurs both in the presence and absence of multipath. The proposed method does not necessitate any hardware modifications; however it does necessitate more autocorrelation function samples for comparison, as with other traditional methods. From the results, it is clear that the given NNDLL performs better than the conventional solution in high multipath situations.

2.7.2. On unmanned aerial systems detection of GPS spoofing attacks

Many civil and military software packages have gained an interest in unmanned aerial systems (UAS). A machine learning method has been

Table 4. Comparison of the different machine learning techniques used in the investigated papers for body centric.

Reference No.	Antenna Used	Algorithms Used	Compared to	Result
[32]	THz antennas	supervised algorithms		Use of the THz band for body- centric networks.
[33]	UWB antenna	linear regression		Absorption of electromagnetic radiation by muscle tissues under radiating near-field circumstances.
[34]	planar antenna	k-nearest algorithm, support vector machine.	linear regression	The system was built with off-the-shelf, non-wearable components.
[35]	TX antenna and Rx antenna	classical machine learning	deep learning	In comparison to other methods, using a wireless signal for standby emotion detection is a better option.
[36]	conventional antenna	ML		Current position of the body- centric communication networks.

proposed to detect GPS spoofing signals based on an artificial neural network. The aftermath shows a low probability of incorrect alarms and a favorable probability of detection.

Depending on various sensors, including the Global Positioning System (GPS), the Unmanned Aerial System (UAS) does its operation. According to [96, 97], and [98], GPS makes UAS an ideal system for tracking and navigation goals with a precision of up to 3 m. For location tracking and time synchronization in real time, GPS is used by several devices. Signals are received by at least four satellites, which act as GPS receivers. Because of the unencrypted signals of the satellite, the public GPS receiver is not secure and cyber-attacks, including GPS spoofing, can happen through those GPS receivers. So cyber-attacks can happen at a higher power, and in the attack, fake signals like satellite signals are transmitted by hackers. The hacker can later rebroadcast the GPS signals that were previously stored. By changing the time delays and information in the signals, an attacker can cause the receiver to calculate a random position. This can be done with minimal software and hardware. In [99], a method based on state approximation analysis using Support Vector Machine was presented to detect GPS spoofing attempts on UAS. However, in the long run, this strategy degrades in performance. Another method in [100] dubbed Crowd-GPS-Sec is used to locate and identify GPS spoofing assaults on aircraft and UAVs. However, this method is not feasible because it takes fifteen minutes to achieve a localization accuracy of roughly 150 m. By this point, hackers have already done their harm. Because traditional solutions have shortcomings, this study proposes a new machine learning method based on artificial neural networks (NN). In this technology, an algorithm analyzes actual or fake GPS signals and makes judgments about the existence or absence of attacks.

2.7.3. Dethroning GPS in low power accurate 5G positioning system

In this study, a Deep Learning (DL) dependent millimeter wave (mmWave) positioning solution's energy consumption is evaluated. Then, with the advanced and accurate outdoor positioning systems, it was later differentiated. With millimeter wave networks, the suggested method reduces the energy requirement for precise pointing. So, for mobile devices, the design provides efficient and accurate positioning.

This research closes the loop on a formally proposed Beamformed Fingerprint (BFF) placement approach for mmWaves by demonstrating energy feasibility across several DL models. This approach achieves an uneven perfection level in the appearance of non-Line-of-Sight (NLOS) (one order of magnitude better than the prior state of the art). This research compares the energy consumption of locating and tracking systems that work using mmWaves. Because fingerprint positioning approaches can share the same precise DL models, a large number of results can be transferred between them. The developed system outperforms GNSS-based systems in terms of accuracy and feasibility.

3. Analysis

For antenna design, machine learning has shown great results, but it also has some issues. Choosing the perfect algorithm for any experiment is a major challenge. Because all kinds of simulation data are not suitable for all algorithms, an unsuitable algorithm may not be able to find the perfect result. So datasets need to be checked first before using an algorithm. Before starting work, we need to know very well what area of the problem we are working on. Because valueless results can be found from wrong assumptions, and it will be a waste of time and resources. Getting a clean dataset is very hard, and getting an accurate result is also necessary. Several simulations have to be done, so that proper training data can be found. Preprocessing data is a difficult task because the data needs normalization and feature selection, and for large datasets, a huge amount of time is needed. Debugging the algorithm for solving a problem is also an important task in the field of machine learning.

To investigate the performance gap between the suggested design and the traditional design, we employed Monte Carlo simulations, where the average is derived using 100 channel realizations, and a total of 1000 symbols are used for each channel realization. Furthermore, the desired or required BER is set to 103 in these results. By simulating the proposed learning-assisted adaptation, we were able to show that it easily fulfills the required BER while giving a much greater data rate than traditional link-adaptation based on SNR threshold values.

In the learning beam codebook, it is capable of optimizing the beam patterns, but in more complicated scenarios it is not applicable. Map-based mmWave channel models have some hardware issues. That's why they are cost-effective. Long-range gesture recognition is also costly for the radar, and the model accuracy is not stable, nor is it tested in different types of scenarios.

In [26], a Reinforcement Learning (RL) technique for spatial beams was developed to maximize the mean data throughput of a multi-antenna wireless system that implies hybrid beam-forming in the millimeter wave frequency band to speed up the selection process. From the result, it is clear that only a fraction of the iterations are required for the RL-based approach. On the other hand, the compared brute force solution

Table 5. Comparison of the different machine learning techniques used in the investigated papers for THz.

Reference No.	Antenna Used	Algorithm Used	Compared to	Result
[37]	PCA	THz DL-CT	THz CT	It shows much superior image quality.
[38]	N_B,N_u, N_R	RFC	SVM	Reduce the computational complexity hybrid beamforming
[39]	Photoconductive	CNN	SVM	Developing identification of metamaterials in mixtures
[40]	Multi-mode multiple antenna	DNN		Demo of 6G mobile network
[41]	UM-MIMO	DNN	Plasmonic antennas, PCA	Future vision of THz communication

Table 6. Comparison of the different machine learning techniques used in the investigated papers for Satellite.

Reference No.	Antenna Used	Algorithm Used	Compared to	Result
[46]	Reflectarrays	SVM	MoM-LP	Accelerate computing time without compromising accuracy.
[47]	Multibeam antenna (MBA)	Branch-and-bound (B&B) and simplex algorithms (SA) are examples of DL-based optimization (DBO) algorithms	Typical data-driven strategies and traditional iterative optimization approaches	The optimization component can ensure the solution's efficiency and increase overall performance while speeding up the method of BH pattern selection and allocation.
[52]	Phased Array Antennas (PAAs)	Deep neural network	Non-linear programming	Large-scale OBFNs can be tuned for any desired delay.
[65]	Satellite Antennas	Reinforcement Learning (RL) algorithm	Traditional satellite-terrestrial networks	Ascertain that our mobile stations and terminals receive the best antenna signal and are subjected to the least amount of communication interference from other stations or terminals.

Table 7. Comparison of the different machine learning techniques used in the investigated papers for UAV.

Reference No.	Antenna Used	Algorithm Used	Compared to	Result
[72]	planar	k-neural networks	support vector machines	Synthesize the research on unmanned aerial vehicles (UAVs) based on a machine learning environment.
[73]	conventional	reinforcement learning		Why, how and which types of algorithms are used in U-RANS
[74]	reflectarrays	k-nearest algorithms		Localization as a classification problem by using machine learning
[75]	mimo antenna	artificial intelligence		Get a detailed overview of the AI's potential applications in UAV-based networks.
[76]	planar	linear regression		Grain yield and protein content are predicted.

necessitates numerous iterations. But there is no clear solution to data security and clean data collection.

Locations, sizes of the receiver, and nearest vehicles were used to determine the ideal beam pair index in [32], which took full advantage of machine learning equipment with previous beam training information. Many levels of situational acknowledgment are a key part of this study, and an inclusive analogy of numerous classification schemes has been addressed. As a result, it is stated that 86% alignment probability can be achieved, but there is always a security concern. A lot of factors can go wrong, and that can lead to missing vehicle locations in the feature. The noisy features are GPS inaccuracy, location updating frequency, and penetration rate.

In [35], a massive multi-input multi-output system using millimeter wave (mmWave) by multiple users for beam alignment has been presented. An alignment approach with partial beams utilizing Machine Learning (AMPBML) has been suggested without any prior information, such as user location details. But there is always an issue of clear data for testing and training. The implementation is also time-consuming.

Every specification of the pre-coders used to obtain the optimum decoder is regarded as a mapping relation in the deep neural network (DNN) in the [39] solution. In this study, a deep learning assisted mmWave massive MIMO architecture was employed for practical hybrid pre-coding. However, because Deep Learning lacks common sense, the system is vulnerable. When mistakes are made, the results can be severe.

An energy-efficient hybrid pre-coding approach utilizing one-bit PSs has been investigated in [41] for practical frequency-selective wideband mmWave massive MIMO systems. Furthermore, as the CEO algorithm for machine learning advances, a cross-entropy optimization (CEO) based hybrid pre-coding technique to optimize the earnable sum rate of the reviewed system has been presented. But for this solution, a huge amount of time and resources are needed. There is also high error susceptibility.

At this moment, the detection of COVID-19 is primarily done via polymerase chain reaction (PCR) tests. However, researchers are looking for advantageous alternative solutions. Besides the detection of COVID-19, there is also a focus on carrying out antibody tests that can help determine a previously infected person, resulting in a better understanding of the virus' spread. Besides using the THz band in imaging for detecting viruses, THz technology can also assist patients' remote operations during a pandemic. For example, THz-based wearable sensors or implants on the patient's body can collect health data at high rates and forward it to the healthcare support staff, where actions can be taken remotely to assist patients. The development of any new technology always raises both positive and negative feelings. Nowadays, the major focus is on 5G technology, and there is a strong belief among a considerable number of people that 5G technology negatively affects human health [57].

The auto encoder model was implemented in a MATLAB tool in this article, and scalograms generated from Wi-Fi signals were used for training, validation, and testing.

They describe the use of next-generation body-centric communication for occupancy monitoring, which can provide a cost-effective and privacy-preserving solution for lowering energy usage and carbon footprint. They used machine learning algorithms; in this section, they didn't give any description of the K-nearest algorithms. In other papers, there are no conflicts of interest.

In the THz antenna with a machine learning approach to 6G network, we can see there are some hardware issues like antennas, so it will be costly. Again, if we see beam selection, there are some assumptions in multi-user uplink, so it is not suitable in all situations. Using THz DL CT is very time-consuming. THz communication will be very flexible in the future, but as we need 6G networks and other hardware, it will become very cost-effective.

A machine learning technique called Support Vector Machines (SVMs) was used to develop and optimize reflect arrayantennas [89]. As a result, computing time is reduced without a decrease in accuracy. The main significance of [89] is that by using SVMs, cross polar isolation and cross polar discrimination can be improved and the computing time remains the same. But there is a problem with a lack of quality data, inadequate infrastructure and resources. SVMs do not work well with large datasets because the required time is higher.

In [90], to simplify feasible beam hopping (BH) in multibeam satellite systems, a Deep Learning (DL) based path was developed. In the satellite coverage area, to manage time variants and irregular traffic requests, BH can maintain flexibility. A learning and optimization approach was used to create a rapid, near-optimal, and viable solution for BH scheduling. But there are some problems with Deep Learning. The duration of development is long, large and clean data is needed, and it is also computationally expensive.

Table 8. Comparison of the different machine learning techniques used in the investigated papers for Textile.

Reference No.	Antenna Used	Algorithm Used	Compared to	Result
[78]	Dual-polarized textile patch antenna	PDF		Hybrid machine learning-based framework
[81]	Folded dipole antenna,	SVM		Knitted folded dipole antenna design and application
[85]	Dipole antenna	CNN	CNN	Clothface technology that can recognize handwriting
[92]	Textile antenna	SUMO toolbox		Overview of SBO

Table 9. Comparison of the different machine learning techniques used in the investigated papers for GPS.

Reference No.	Antenna Used	Algorithm Used	Compared to	Result
[93]	GPS antenna	Neural network (NN)	Conventional early-minus-late DLL, narrow correlator, and high resolution correlator.	In high multipath situations, the NN-based DLL generates lower code phase root mean squared error than the three traditional approaches (standard early-minus-late DLL, narrow correlator, and high resolution correlator).
[95]	GPS SMA antenna	Neural network	Support Vector Machine and Crowd-GPS-Sec	It has a high likelihood of detection and a low likelihood of false alert.

A deep neural network model of tuning Optical Beamforming Networks (OBFNs) was devised in [95]. Small and flat Phased Array Antennas (PAAs) must be tuned for OBFNs in order to receive signals from space, allowing planes and satellites to communicate. But problems can be faced with repairing and maintaining satellites. Also, much more data is required in neural networks than in traditional machine learning algorithms.

An artificial intelligence (AI) based pointing and tracking method for mobile terminals and stations in satellite terrestrial networks was developed in [108] to ensure that mobile stations and terminals experience minimal communication interference and can access ideal antenna signals from other stations or terminals. But there are also some limitations, and those require supervision, cost, and maintenance. There is no one-size-fits-all solution.

In [115], the use of AI in satellite communication has been discussed. There is no practical application for this study.

The research on combining unmanned aerial vehicles and machine learning is still in its early stages. The current study discovered that research in this area is inconsistent, with the majority of it relating to computer/wireless networks, smart cities, the military, agriculture, mining, and statistical analysis of wild life. In UAV, the random forest and support vectors have been employed in different ways. It can be done on a model for detecting and identifying unregistered consumer UAVs, and trained machine learning models for recognizing objects in UAV and satellite imagery can also be constructed.

Deep RL can also be used to adjust the speed of the UAV cloudlet (s) dynamically in order to improve user performance. When the derived solutions operate on data with different properties than the data used to train the model, the performance of Machine learning techniques may be reduced or unanticipated behaviors may occur. They can also obtain resource location information more quickly and efficiently using this method.

It should be noted that machine learning tools are frequently used in the literature to solve problems that could be solved in a more simple and deterministic manner, giving the impression that the need for machine learning is not well justified, which could lead to machine learning misapplication in many cases.

In this paper, they can also use machine learning algorithms and re-identification using the features of each target. In the future, the pattern of the animal's skin and the shape of the animal's body can be considered.

In textile antenna design, all of the work is focused on the flexibility of textile areas. In the UQ method, some random variables are introduced, but not all the variables are used to show the result. In cloth face technology, it is cost-effective as there are some hardware issues. The SBO method has not been experimented with on other antennas.

In the simulation result of the proposed NNDL is compared to that of traditional code phase tracking solutions such as E-L DLL, HRC, and narrow correlator. While the NN outperformed traditional approaches in a multipath environment, the NNDLL was shown to be able to match the performance of traditional code phase tracking approaches when multipath was not present. With genuine GPS signals, the NNDLL was able to achieve nearly half the RMSE of an E-L DLL while being trained with simulated GPS signals. But there are many problems with neural networks, and those are the large amount of data needed, the lack of clean data, and the computationally expensive nature.

Based on an artificial neural network, proposes a machine learning method for detecting GPS spoofing signals. But there are some problems that can be faced by this solution, and those are high error-susceptibility and a lack of skilled resources.

In the Deep Learning dependent millimeter wave positioning solution's energy consumption is evaluated. But some issues can be faced with these problems, such as the long duration of development, the huge amount of data needed and the cost. DL systems are fragile and when errors are made, the errors can be huge (see Tables 3, 4, 5, 6, 7, 8, and 9).

4. Conclusion

This paper provides an overview of the uses of machine learning, deep learning, and artificial intelligence in antenna design. A comprehensive study was conducted on various antenna designs, and we found that the newly developed methods of antenna design by machine learning, deep learning, and artificial intelligence give better results than conventional methods. We explored the fields of millimeter wave, UAV, THz, satellite, textile, body centric, and GPS for antenna design. We found that the use of machine learning, deep learning, and artificial intelligence can save time and, with the minimization of errors, can provide high accuracy for the above fields of antenna design and also speed up the antenna design process. In this study, fewer simulations, efficient antenna behavior prediction, and less computational time have been seen in the field of antenna design by machine learning, deep learning, and artificial intelligence.

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