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Deep Learning-Based 5G Networks and IoVs: Advances, Meta-Data Analysis, and Future Direction

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Abstract: The emergence of 5G wireless networks is intensifying competition and driving a growing demand for network capacity to support a multitude of devices running data-intensive applications that rely on uninterrupted connectivity. This escalating need for network capacity is crucial for handling multiple devices simultaneously, and it holds the promise of significantly benefiting evolving business models in the wireless network market, which is striving for increased accessibility. Moreover, the early stage of 5G technology has compounded these challenges, rendering the strategies employed thus far less effective in addressing these newly prominent issues.

Consequently, research endeavors have been concentrated on the utilization of deep learning algorithms to address the challenges confronting 5G networks and the Internet of Vehicles (IoVs) powered by 5G. In this paper, we delve into research exploring the use of deep learning algorithms to resolve issues that arise within 5G mobile networks and the convergence of 5G and IoV, with the aim of tackling the complexities that can arise in this technological intersection. Our survey reveals innovative developments in deploying deep learning models for problem-solving within 5G mobile networks and the 5G-powered Internet of Things. These deep learning algorithms provide solutions for a wide array of areas, encompassing security, energy management, resource allocation, 5G-enabled Internet of Things, mobile networks, and more, all within the context of 5G communication systems. Recent progress has also been made in enhancing and expanding existing taxonomies, as well as introducing new taxonomies, supported by thorough research and presentation. The previous research analyzed and deconstructed the limitations of the techniques, and this article introduces and explores a novel perspective point for addressing those concerns. The previous research looked at the problems of the techniques. We anticipated that our study would pique academics' curiosity in deep learning's real-world applications in 5G networks and point them in the right direction for developing innovative solutions.

Keywords: *5G; cloud-based; energy-efficient; key performance indicators; RAN*

1. Introductory Paragraph

Over the past two decades, there has been substantial progress in cellular communication technology, transitioning from 2G GSM to 4G LTE-A. This evolution was driven by the growing need for increased bandwidth and reduced latency. Throughput, which signifies the rate at which data is transmitted, and latency, influenced by the processing speed of each node, have been crucial considerations. When devising new mobile technologies, developers take into account factors such as jitter, inter-channel interference, connectivity, scalability, energy efficiency, and compatibility with previous network standards.

The shift from 2G to 3G with UMTS brought about real-time video communication, thanks to enhanced network speeds and reduced application-server latency. The advent of LTE and LTE-Advanced (LTE-A) further expanded network capacity and decreased latency, making it possible to access triple-play traffic (comprising data, audio, and video) wirelessly at any time and location. While 3G primarily catered to telephony with some multimedia and data capabilities, 4G represented a leap towards mobile broadband. Notably, 2G was the pioneer in digital mobile voice standards, aimed at extending coverage. The data rates for 2G, 3G, and 4G were 64 kbps, 2 Mbps, and 50-100 Mbps, respectively.

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The impending 5G technology is expected to enhance the scalability, connectivity, and energy efficiency of mobile networks. By 2020, it's anticipated that 50 billion devices will be connected to the global IP network, raising concerns about managing this massive network. In a fully "networked society," various appliances and business machinery could be remotely controlled in real-time via a reliable 5G network, presenting exciting prospects for the Internet of Things (IoT). The development of energy-efficient network nodes is also underway to meet the demands of 5G.

5G boasts features like high throughput, low latency, reliability, scalability, and energy efficiency. This article delves into several 5G techniques and discusses 5G use cases, research groups, and research initiatives. The subsequent sections offer comprehensive insights into these topics, concluding with some final thoughts.

The escalating demand for ultra-fast mobile communication is driving the development of novel mobile communication technologies. These advances are geared towards achieving high data transmission rates and supporting applications that necessitate new wireless radio technologies. Moreover, high-speed satellite communication is also becoming a part of this ecosystem. Radio's role in adaptive learning and decision-making has the potential to facilitate the management of the expanding wireless mobile network. The introduction of 5G wireless mobile networks is poised to trigger innovative developments in video surveillance, high-speed stream processing, and highly secure network connectivity, impacting fields such as video surveillance and the Internet of Vehicles (IoV).

The next generation, 5G, promises low latency and high bandwidth, providing consistent connectivity wherever needed. It is expected to benefit various industries, particularly with the Internet of Things (IoT) contributing to a tenfold increase in internet traffic. However, the complexity of 5G wireless mobile networks, in terms of applications and settings, necessitates the use of cutting-edge AI-driven computing solutions to address associated challenges.

The intersection of AI and 5G research and development is already underway in preparation for the 2020 deployment of 5G technology. This AI renaissance may introduce new problem-solving methods that surpass previous approaches. Machine learning, a form of artificial intelligence, holds promise for enhancing 5G wireless mobile network technologies, as it has already done for 4G networks. The advent of artificial neural networks and deep learning algorithms, which can perform on par with human specialists, offers solutions for handling large-scale data from mobile tasks, particularly in speech recognition and computer vision, as mobile tasks generate massive volumes of data. This makes deep learning algorithms well-suited to addressing large-scale challenges in 5G wireless mobile networks as data collection continues to grow. Because there are more connected autos than ever before, data transmission via traditional networks is more likely to be delayed, with a decline in packet delivery and network congestion. These problems are being caused by linked autos. The Internet of Things and intelligent transportation were coupled to develop the IoV, which fosters data sharing with its surroundings. This was made possible via the Internet of Vehicles. Wireless communication networks enable data exchange between automobiles, infrastructure, roadside equipment, sensors, and personal electronic devices [18]. These applications have been referred to as "vehicles to everything" [19]. Deep learning architectures [20] employed within the domain of 5G are instrumental in addressing challenges in areas such as cybersecurity, resource management, energy optimization, mobile networks, and the Internet of Things enabled by 5G. These deep learning techniques encompass various models, including convolutional neural networks (CNN), generative adversarial networks (GAN), dense neural networks (DDNN), deep reinforcement learning (DRL), long short-term memory (LSTM), autoencoders (AE), and deep recurrent neural networks (DRNN). In this paper, we delve into the evolution of deep learning algorithms and their applications in devising solutions for 5G wireless mobile networks and the Internet of Vehicles powered by 5G. Our examination will center on the advancements in deep learning as it pertains to generating solutions for 5G-enabled IoV. This assessment is built upon existing published literature.

2. Future 5G Scenarios

The year 2020 will mark the advent of a new era in connectivity. The Internet of Things, coupled with advanced and interconnected sensor technologies, will fundamentally transform the way people lead their lives. This "smart living" paradigm will necessitate a constant and ubiquitous mobile network connection to upload activity data and IoT control instructions, resulting in a substantial increase in uplink data flow, often referred to as "huge reporting" [2]. Machine-to-machine communication will become paramount for a wide range of services, businesses, and industries.

Vehicle ad hoc networks (VANETs) are continually improving, and by 2020, they will be integrated with cellular networks to create a VANET cloud, thus enhancing and securing transportation [3]. The offloading of networked data into unlicensed frequency bands will play a pivotal role in balancing network load over the next decade. This approach will provide guaranteed bit-rate services while reducing control signaling, making it a significant development in the coming years. To meet the real-time traffic demands and ensure the satisfaction of end-users, 5G technology must seamlessly integrate with densely populated heterogeneous networks [4].

3. Research teams

The METIS project has recently released its final report (Deliverable 8.4, April 30, 2015), which encompasses research on architecture, high-level architectural visuals, a channel model, over 140 technology components, and testbed evaluations [6]. They have demonstrated the flexibility of air interfaces using FBMC (filter bank multi-carrier) technology. Their simulation study evaluates critical 5G key performance indicators (KPIs), including subscriber traffic, area traffic, average user data rates during peak hours, and actual user data rates, with RAN latency below 1 millisecond. They have also presented RAN structures and traffic flow scenarios in interior offices, retail malls, stadiums, and busy outdoor metropolitan areas. METIS-II aims to achieve a comprehensive 5G RAN design, collaborative review, and global consensus among standards bodies, with involvement from the European Commission, manufacturers, telecom companies, and academia through 5G-PPP. The vision is for telecom and IT to converge into a single infrastructure with integrated fixed and mobile access within the next ten years [7].

The 5GNOW project has explored various aspects, including uniform frame structures, low latency, high reliability, and 5G waveforms. In their most recent delivery, they introduced Gabor signaling, where the larger signal is composed of scaled time-frequency variations, with scaling factors determined by Gabor expansion coefficients. They also demonstrated the use of the short-term Fourier transform (STFT) for identifying the time and frequency characteristics of a signal [8].

Emphatic's research has delved into MIMO (Multiple Input Multiple Output) transmission, equalization, configurable filter banks, and multi-hop or relay-based communication protocols. Their recent project deliverables included papers on MIMO transceiver techniques for FBMC in frequency-selective channels [9] [36][37].

The NEWCOM project focuses on advanced possibilities in wireless communications and networking, addressing topics such as wireless network constraints, opportunistic multi-hop communications, and energy and channel efficiency. Among their recent breakthroughs are original research on mobile broadcasting, Cloud-RAN (Radio Access Network), 4G/5G coexistence via spectrum overlay, multi-hop coding, and localization using distributed antennas. The study participants have discovered that factors such as system bandwidth, modulation coding technique (QAM), and the implemented resource block significantly impact baseband processing outcomes [10] [38][39][40].

4. Wireless At Nyu

Leading the research on mm-wave technology for 5G is Rappaport and his team, who conducted extensive investigations into mm-wave propagation and path losses in urban areas such as New York and Austin [11]. In the United Kingdom, the 5G Innovation Centre (5GIC) has achieved remarkable wireless Point-to-Point (P2P) communication speeds of 1 Tbps, contributing significantly to 5G development. Their future plans encompass the deployment of ultra-low latency application services [12] [41].

Meanwhile, the Electronics and Telecommunications Research Institute (ETRI) in Korea is diligently working on enhancing the GIGA 5G project, focusing on improving dependability, the mobile hotspot network (MHN) protocol stack, and device-to-device (D2D) communication technologies [13, 14]. South Korea's 5Gforum is actively fostering new industrial innovations and conducting research to shape the future 5G standards. In the United States, the influential voice in the realm of 5G is 4G-Americas, which publishes white papers and provides recommendations emphasizing information-centric networking (ICN) as a key aspect of 5G development.

It's worth noting that the research organizations mentioned above are just a subset of the numerous organizations contributing to 5G research. Pirinen briefly discusses some of these organizations and their work [15]. In the following section, we will delve into the technical advancements in 5G [42].

5. Evolution of 5G

In the development of 5G technology, it is possible to adapt several well-established technologies or methodologies, such as modulation techniques, radio access methods, or distributed computing, with minor adjustments. In addition to these adaptations, a multitude of entirely new solutions are being created from the ground up. This approach involves a focus on the most recent research articles, white papers, industry products, and the specific requirements of clients [43][44].

One valuable source of information is the Visual Networking Index (VNI) white paper, which is released annually by Cisco Inc. The most recent Cisco VNI research, published in February 2015, provided projections for global mobile data traffic. According to these projections, by 2019, global mobile data traffic will approach 24.3 Exabytes (EB), which is ten times the current volume, and the number of connected devices will soon surpass the world's population [16]. Cisco VNI offers insights into the anticipated flow of mobile data.

6. Transmission of Millimeter Waves

The development of 5G technology begins with the utilization of the millimeter-wave spectrum, which operates with wavelengths in the millimeter range, and the opportunistic use of unlicensed frequencies. To initiate this, the first step involves employing 5 GHz Wi-Fi frequencies. Traditional cellular carrier frequencies fall within the range of 750 to 2600 MHz. The goal is to establish efficient millimeter-wave physical layers that are underutilized. Key techniques such as Massive MIMO, beam shaping, offloading traffic to unlicensed bands, and the cloudification of radio resources will enhance the speed and reliability of data transmission. It's important to consider how urban structures affect carrier propagation, penetration, and route losses at 28 and 38 GHz, which will inform the development of the physical (PHY) layer for 5G millimeter-wave networks. Additionally, Levanon et al. have developed a 5G millimeter-wave system that reduces latency [17] [45][46].

In the context of 5G, the core and radio access network

(RAN) will be closely integrated. Base stations will need high-bandwidth connections, and the backbone network might transition from fiber to millimeter-wave wireless connections. As the number of connected devices in a typical macro-cell increases, the architecture must be adapted to accommodate greater signaling and payload overhead. Giga KOREA 5G evaluated the performance of a 5G architecture using millimeter-wave RAN and provided graphical representations of antenna array topologies for 3D beam-forming, as well as insights into the beam management mechanism for rapid beam handover.

In terms of radio access technology, 2D patch antenna arrays are capable of generating 3D beams, which enable highly focused radio transmission signals. These are useful for techniques like Space Division Multiple Access (SDMA) and Beam Division Multiple Access (BDMA). Each array is equipped with 2D NXM patch antennas, providing a long-lasting, secure, and dependable radio access method that facilitates quick beam handoff. To expand the coverage of millimeter-wave RANs, "relay" transmission is employed, and the control of handoff may shift from the core node to the base station [47][48].

Resource allocation in 4G LTE is managed by the eNB (evolved NodeB). Various scheduling techniques have been proposed to enhance the Quality of Service (QoS) for LTE. Game-theoretic resource allocation strategies have been introduced for cognitive radio connections [18]. In cases where beamforming is not an option, 5G should utilize the most suitable resource distribution strategy. The goal is not only to achieve increased RAN capacity but also to establish a flexible, intelligent, simple, and cost-effective core network. Recent developments in cloud networking have enabled virtualized core networks.

Two essential considerations for 5G technology are:

a. Modulation Technology: A superior modulation technology is needed, surpassing Orthogonal Frequency Division Multiplexing (OFDM). The choice of modulation significantly affects spectral efficiency. While OFDM modulation and Orthogonal Frequency Division Multiple Access (OFDMA) are used in LTE-Advanced (4G), 5G requires modulation techniques that can handle a high peak-to-average-power ratio (PAPR) and cyclic prefixes to avoid inter-block interference. It's also uncertain whether OFDM can be effectively used in conjunction with broadband millimeter-wave technology. Comparative studies have been conducted to evaluate modulation techniques for 5G, including Filter Bank Multicarrier (FBMC), Universal Filtered Multicarrier (UFMC), and OFDM [19].

b. Energy Conservation: Energy consumption is a critical aspect of new network deployments, given that mobile networks currently consume approximately 0.5% of the world's energy.

These considerations represent crucial elements in the development of 5G technology.

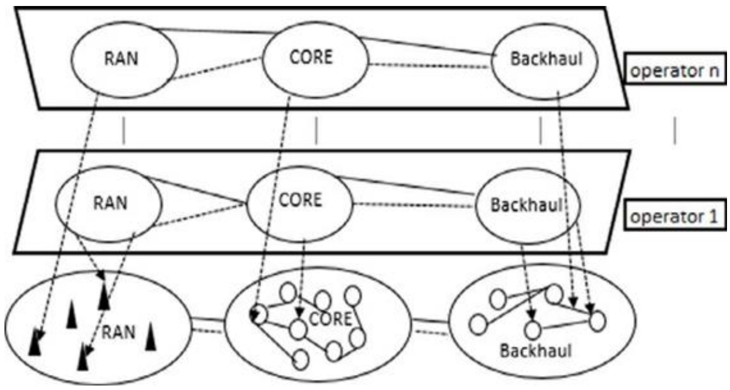


Fig 1 is a schematic representation of the cloudification of a network.

Observation 1: DL-based channel estimation models exhibit susceptibility to adversarial attacks, with a particular focus on BIM, MIM, and PGD attacks, among which BIM stands out.

Observation 2: In terms of the success rate of attacks, BIM, MIM, and PGD prove to be the most effective assault methods.

Observation 3: It is worth noting that DL-based channel estimation models show greater resilience against C&W attacks, as demonstrated in the third observation.

Observation 4: A significant, inversely proportional relationship between the power employed in an attack and the accuracy of channel estimation models becomes evident.

Observation 5: The provided mitigation approach, known as defensive distillation, exhibits superior performance in countering hostile attacks.

Algorithm Distillation Pseudocode:

Here is the pseudocode for the Algorithm Distillation process, which involves training a student model (S) based on a teacher model (T) using a defined loss function (L), learning rate, and specified number of epochs (E):

```python

Teacher model T, student model S, loss function L, learning rate, epochs E

S, the student, is trained as follows:

Initialize S's weights for e = 1 to E:

For each epoch, randomly shuffle the dataset D from 1 to jDj:

For each sample (xi, yi) in D:

- Forward propagate xi through T to obtain Yi's output probability.

- Calculate L using yi.

- Backpropagate L through S.

- Update the weights of the student model S using the specified learning rate.

End the inner loop.

End the outer loop.

Return the trained S-model student.

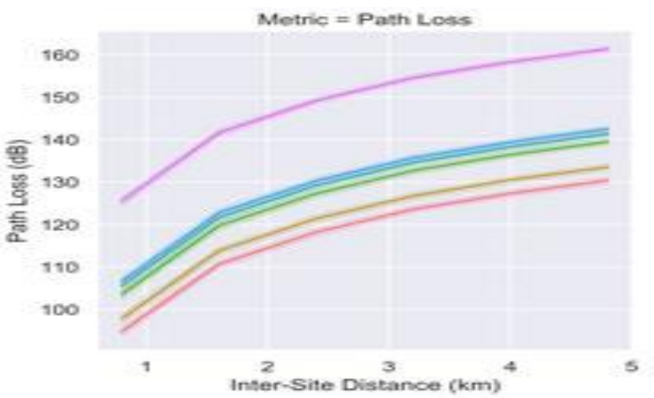
Reducing energy consumption is a pivotal aspect of 5G, with implications for both environmental sustainability and network maintenance. Tomaz and Sung [28] provide numerical evidence that densified networks must meet energy requirements, particularly due to the increased presence of microcells, with the majority of network energy consumption occurring during idle periods and backhauling. The implementation of 5G can benefit from software-defined Medium Access Control (MAC) and network functional virtualization, potentially leading to a low-latency, energy-efficient 5G network when these technologies are combined. Their analysis aligns with the 5GrEEn Project, as discussed in [2], which emphasizes the logical separation of control and data planes as a means to achieve an energy-efficient and flexible 5G architecture. The 5GrEEn Project focuses on increasing network capacity by establishing an energy-efficient and optimized heterogeneous network architecture (HetNet) capable of accommodating diverse traffic requirements and scenarios, along with the proper allocation of cloud resources. In this context, the introduction of the Anchor platform is noteworthy as a novel cloud-based resource management platform [30] [49].

## 7. Work Proposal and Results

The MATLAB 5G Toolbox is a valuable resource that includes references and visual aids related to 5G technology [37]. It allows for the creation of DL-based models using customized waveforms, antenna configurations, and channel models. In this work, a DL-based channel estimation model was trained using a dataset. An illustrative example from the MATLAB 5G Toolbox is the "Deep Learning Data Synthesis for 5G Channels," which demonstrates the generation of 5G channel data. In this specific case, a convolutional neural network (CNN) is employed to estimate channels, with the use of SISO (Single-Input Single-Output) antennas. To perform channel estimation, PDSCH (Physical Downlink Shared Channel) and DM-RS (Demodulation Reference Signals) are necessary components.

The reference example provided by the Toolbox includes 256 training sessions. During these sessions, 256 signals are transmitted and received while employing DL-based channel estimation. Each recorded data point consists of 8568 data values, which are categorized as follows: 1 antenna, 612 subcarriers, and 14 OFDM (Orthogonal Frequency Division Multiplexing) symbols. Each training data point is transformed into a structured 612-14-2 matrix, serving as inputs for the neural network during the training process.

In real-time, the CNN model maintains a resource grid composed of actual and complex data points, creating a two-dimensional representation. The training dataset undergoes necessary modifications to facilitate the learning process.




4-dimensional array, i. H. 612-14-1-2N, where N represents a number of training examples, i.e., 256.
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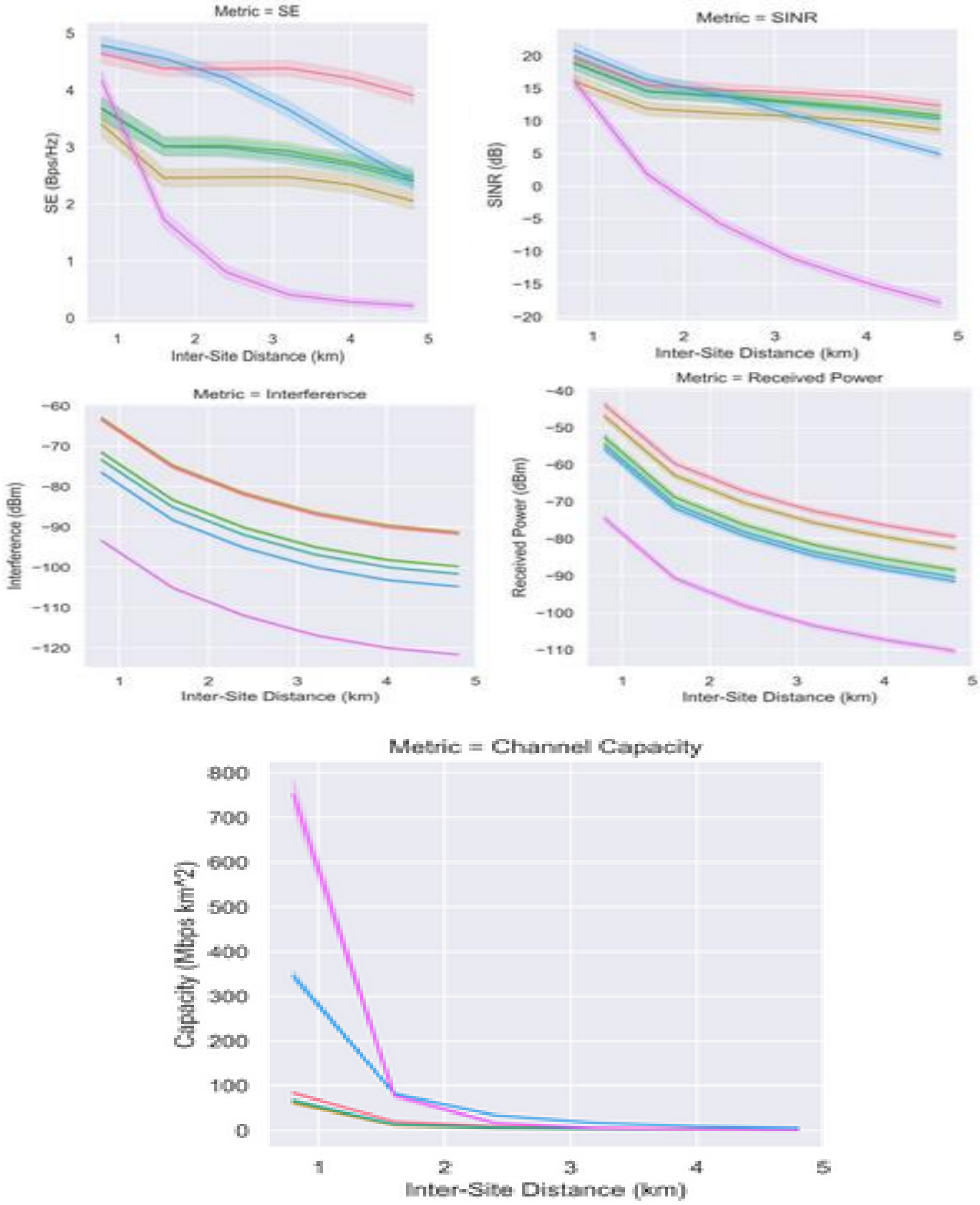

The first experiment involves launching attacks on targets lacking sufficient defenses, as depicted in Figure 3. The results of this initial experiment reveal that the initial DL 5G model is indeed vulnerable to machine learning attacks initiated by adversaries. As expected, the achieved Attack Success Rate (ASR) justifies the adversary's efforts. The results also highlight the effectiveness of attacks such as BIM, MIM, and PID, as demonstrated in the findings.

Figure 4 presents a spectrum of six distinct values (0.0, 0.1, 0.5, 1.0, 2.0, 3.0) showcasing the vulnerability of the DL 5G model and the defended DL 5G model based on distillation, which is prepared to counter any attacks. In the case of C&W attacks, represented by line charts, no substantial variance is observed. Consequently, this proposed technique has the potential to enhance the accuracy of channel estimation models, making them more resilient to adversarial attacks. Figure 5 illustrates the Mean Squared Error (MSE) variance for each of the different values. The figure demonstrates how each attack relies on the vulnerability of the defensive distillation model. The MSE score for the defensive model (on the right) remains virtually consistent for every attack and value, emphasizing the effectiveness of the distillation as a defense mechanism. This method proves to be highly efficient against various types of adversaries.

8. Conclusion

This article provides a detailed assessment of various recent projects that are working toward a 5G mobile communication standard that is flexible, environmentally friendly, and substantially dominating. The initiatives have been working toward this standard since very recently. It was briefly discussed how important concerns such as the research efforts being made to produce a superior alternative for OFDMA and more energy-efficient D2D communication are. On the other hand, owing to limitations imposed by the available area, there are a great many subjects that could not be covered in more depth. It is conceivable for DCCN to replace DFT/IDFT in circumstances in which it is implemented as different streams. This is accomplished by using the multiplication rule in complex fields rather than dealing with the real and imagined components of IQ samples. OFDM technology, while also taking advantage of the redundant information that is offered by cyclic prefixes. throughout the OFDM waveform in order to get a better signal-to-noise ratio. Taking into consideration the expressive capacity as well as the synergistic effect that neural networks with complex values bring about It is possible for DCCN to combine the responsibilities of CP-exploitation, low-rank approximation of the LMMSE, as well as interference between symbols mitigation, and as a result, it can outperform the conventional receivers with LMMSE as well as the more traditional CP-enhanced channel estimate in doubly-selective Rayleigh fading channels, at a lower frequency, with a higher O's level of computational complexity. This is possible because DCCN is able (N2). In addition, the profession teaches transferable abilities that may be used in future endeavors of a comparable kind. In order to get an approximation of the implementation of complex-valued convolutional networks, practical recommendations are provided as a framework. These guidelines focus on the adjustment of the dimensionality with reference to the parameters of a convolutional layer in terms of the OFDM system. Several novel methods of pedagogical teaching are developed and implemented. In the context of a wireless transceiver that is based on deep learning, the incorporation of a strategy for transfer learning, which is frequently referred to as an end-to-end loss function, has the potential to circumvent the problem of disappearing gradients during training, as well as the utilization of models with mixed signal-to-noise ratios and fading in order to smooth the loss landscape. This is an example of the processing power that may be achieved with a deep neural network. complicated transmission waveform, which may be interpreted as suggesting the following: The FFT processor that is typically found in an OFDM receiver may be swapped out with one that is realized in the physical world.

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