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Optimizing Performance and Security in Information Systems by Adopting Artificial Intelligence and Data Analysis

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Abstract: The use of artificial intelligence (AI) techniques and deep learning based on data analysis for the design and management of emerging communication networks is justified by the increasing complexity of communication systems, conditioned by the diversity of technologies, services, and use cases with different technical requirements. This study is a documentary review that describes the usefulness of artificial intelligence and data analysis to improve both performance and security in information systems, presenting a trend in the present day of countless scientific contributions of AI and its application in wireless communication systems. Traditionally, the classical way of studying improvement has focused on the performance of wireless transceivers under the paradigm of dividing and conquering signals. The paradigm shift comes from artificial intelligence, which has been used to improve real-time wireless communication by analyzing previous data and user preferences. In addition to combining information security with its overall capabilities for risk management, virus prevention, and intrusion detection, it is intended to establish that by unlocking the potential of a wireless network orchestrated by the use of AI, it is possible to maximize resource use and minimize costs, requiring access to and analysis of large amounts of network data. Therefore, continuous updating of data is important for building successful and efficient wireless communication systems.

Keywords*: Optimization, Information Systems, Wireless Networks, Performance, Security, Artificial Intelligence; Machine Learning; Deep Learning*

1- Introduction

The recent evolution of services and varied uses of information systems that allow the transmission of data between devices by electromagnetic waves. In this context, it must refer to wireless communication networks that have generated complex systems that require careful designs and operations to provide an immersive experience for users while keeping investment and operation costs low.

The increasing complexity of these networks makes planning, optimization, and organization challenging tasks. Advances in the modeling of digital and analog transceivers, as well as in network functions, have been significant, but traditional optimization models fall short in the landscape of fifth and sixth generation wireless networks (5G and 6G) by not considering overall end-to-end performance or interactions between processing blocks. In this context, artificial intelligence and machine learning techniques offer new possibilities by harnessing large amounts of data to operate complex systems without relying solely on tedious mathematical models and limited simulations. Deep neural networks and modern learning theories can allow computers to learn models and apply more advanced optimizations.

By virtue of the above, it is crucial that the scientific community that addresses the development of information systems highlight specific research techniques with useful guidance to contribute to the debate on artificial intelligence. Setting the goal of rethinking current ideas, practices, and assumptions. It is also necessary to explore related fields to establish distinctions between previously studied and unexplored topics, identify complex issues, and leverage the combined body of knowledge across disciplines [1].

Although these technologies and techniques are frequently combined in real-world scenarios, the discussion arises about how researchers should focus on information systems and discern novel and distinctive aspects of artificial intelligence technology in their methodologies to be able to separate artificial intelligence from analytics, automation, or other technologies. Therefore, we start by asking the following questions: First, is it still relevant in practice to distinguish artificial intelligence from similar technologies and how these should be used? Second, what should be the guiding objectives, degree of analysis, outcome, context, and value of any definition for it to be useful? Third, what classifications or levels must the data meet to satisfy the requirements of relevance and rigor? Fourth question: What proportion of models or algorithms should be presented in research based on artificial intelligence for addressing information systems? And finally, how can

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information systems researchers evaluate the results of artificial intelligence?

In this scenario, the compilation of empirical research findings on artificial intelligence is needed to simultaneously inform the technological and social components with theoretical foundations and explain these events through studies that provide a convincing underlying logic and justification, that is, a theoretical scroll [2]. While it is recognized that user behavior (such as over-reliance, abuse, or lack of use) also affects system performance, it must therefore be interacted with by artificial intelligence practices. For example, Teodorescu et al. (2021) [3] argue that several key principles of classical information systems theories and ideas should be reviewed in light of the significant distinctions between data-driven techniques and the human-computer interaction of conventional code-based information systems.

In support of these statements, the objective of this article has been to present the developments of professionals and researchers in the area of engineering focused on information systems concerning the optimization of performance and security in wireless networks through the use of artificial intelligence and data analysis as a complementary paradigm focused on model building. Correspondingly, the organization of the sections is described below: Section referring to the research methodology, followed by a section that describes the state of the art in optimizing performance and security in wireless networks through the implementation of artificial intelligence. The next section develops data analysis in 3GPP mobile networks with respect to data-based and model-assisted artificial intelligence techniques with machine learning, as suggested by [4]. Then, in the discussion section, conclusions and relevant references are addressed.

2. Materials and Methods

This documentary study is the product of content analysis based on a systematic review focused on the implementation of artificial intelligence techniques and data analysis to optimize performance and security in information systems, specifically wireless networks. In the review, keywords were used to search for publications in several databases, including Scopus, Springer, IEEE, Google Scholar, Wiley, Science Direct, and ACM. As for the keywords, they were defined based on discussions in wireless network performance categorization, security, artificial intelligence, and data analysis. The submitted articles were further examined after the first evaluation. In this review, you will find articles related to performance optimization strategies in wireless networks based on artificial intelligence collected through bibliographic searches in digital repositories. This sheds light on the development of artificial intelligence and the functioning of security in wireless networks. Articles written in English were included in this study to examine some publications that allow us to understand and capture how machine learning works and what additional studies have been developed to advance the field.

3. Literature Review

This section reflects the developments and contributions from researchers in the optimization of wireless networks as complex information systems through the implementation of artificial intelligence techniques as consequences of empirical developments. This fact focuses this research on artificial intelligence in automated resources that require optimization of performance and security, categorizing the various technologies according to the application area. By using artificial intelligence as a digital agency, or even as a computational digital agent, scholars can address social connections and repercussions on institutions and institutional logics through automation activities or processes.

3.1. Optimization of wireless networks based on artificial intelligence

The traditional approach to improving the performance of wireless transceivers is based on the concept of divide and conquer. The transceiver is divided into signal processing blocks that perform functions such as channel equalization, demodulation, and error correction, which are optimized independently with limited consideration of the interaction between blocks [5]. For the optimization of each signal processing block, well-established mathematical models are usually used, derived from extensive research in information theory, signal processing, and statistics in recent years [6], as reflected in Table 1. However, some of these models, despite being very precise, can be mathematically complex and difficult to apply in real time. For example, MIMO detectors and precoders can be optimally designed using a maximum a posteriori criterion, but this involves solving NP-hard problems. Therefore, often only suboptimal techniques, such as zero forcing compensation, can be used practically [7].

Some manageable models may be too simple and inadequate to accurately capture all the complexities of the wireless propagation medium and the nonlinearities and imperfections of the hardware components [4]. Overall, the existing block-based transceiver structure associated with block-based mathematical optimization compromises transceiver performance in terms of simplicity and manageability, something that AI-based techniques aim to address. In this sense, machine learning can be used to directly optimize the overall performance of the system by treating it as a black box. This is commonly known in the literature as a purely data-driven technique [4]. Therefore, contributions to models to optimize the performance of wireless networks in real time with capacity parameters in the system to process a task in a time of less than 10 milliseconds (ms). And the contributions in models to optimize the performance of wireless networks in almost real time from 10 milliseconds to 1000 milliseconds and in the case of optimization in system capacity in non-real time with more than 1000 milliseconds (see table 2).

Table 1. Studies that use model-based artificial intelligence techniques to optimize the performance of wireless networks in real time (less than 10 ms).

Author	Information system approach	Artificial Intelligence Technique	The purpose of the study
Ye at al.[8]	Signal detection and symbol transmission in orthogonal frequency division multiplexing systems	Estimation and detection based on deep learning.	Channel estimation and signal detection in OFDM systems through the power of deep learning.
He et al.[9]	Multiple -Input- Multiple -Output) technology.	Model-based deep learning (DL).	Detect MIMO by deploying an iterative algorithm and adding some trainable parameters using deep linear MMSE channel deployment for channel equalization.
Shlezinger et al.[10]	Symbol detection in digital receivers based on channel state information (CSI).	Viterbi algorithm in a system that uses deep neural networks (DNN) based on deep learning.	Symbol detection using a deep learning-based Viterbi algorithm.
Soltani et al.[11]	Estimation of channels in communication systems.	Deep learning.	Channel estimation based on deep learning.
Burse et al.[12]	Channel estimation.	Artificial neural networks (ANN) such as multilayer perceptron, functional linkage ANN, radial basis function and its variants in modeling non-linear channel equalization phenomena.	Systematic review of channel equalization using neural networks.
Wen et al.[13]	Estimation of channel structure from training samples.	Deep learning to develop CsiNet compressive sensors.	Deep learning for massive MIMO feedback on downlink channel state.
Yang et al.[14] Arnold et al.[15]	Channel predictions based on downlink channel state information (CSI).	Deep learning.	Deep learning based downlink channel prediction for FDD massive MIMO system.
Jiang et al.[16]	Multi-antenna fading channel prediction.	Artificial neural networks.	AI-powered multi-antenna fading channel prediction
Gruber et al.[17]	Decoding random and structured codes, such as short polar codes of speed 1/2 and block length N = 16.	Deep learning.	Channel decoding based on deep learning.
Cammerer et al.[18]	Resulting non-iterative channel decoding algorithm.	Neural network decoding of polar codes with belief propagation length N = 128.	Deep Learning-Based Decoding Scaling of Polar Codes Across Partitions
He et al.[19]	Turbo decoding of channels in the traditional max -log-maximum a posteriori (MAP).	TurboNet model-based deep supervised learning architecture.	Model-based DNN decoder for turbo codes: Design, simulation, and experimental results.
Blanquez -Casado et al.[20]	Optimal signal-to-noise ratio regions for adaptive	Logistic regression.	Link adaptation mechanisms based on logistic regression models.

	modulation and coding (AMC) over a set of correlated subcarriers in 5G wireless systems.		
Luo [21]	Link adaptation, adaptive modulation and coding (AMC).	Supervised k-nearest-neighbors learning and support vector machines (SVM).	Supervised learning techniques for adaptive modulation and coding
Liaskos et al.[22]	Performance in wireless communications systems.	Deep neural networks (DNN).	Design and control the behavior of wireless environments in a deterministic and programmable way.
Elbir et al.[23]	Estimating direct and cascade channels in RIS reflective intelligent surface-based communication.	Convolutional neural network (CNN) architecture.	Deep channel learning for large smart surfaces Assisted massive millimeter wave MIMO systems.
Taha et al.[24]	Coverage and speed of future wireless systems in phase change design on RIS reflective smart surfaces.	Deep learning	Enabling large smart surfaces with compressive sensing and deep learning.
Thilina et al.[25]	Binary spectrum sensing for cognitive radio networks.	Unsupervised and supervised machine learning used for pattern classification: K-means clustering, Gaussian mixture model, support vector machine (SVM), and K-weighted nearest neighbor.	Machine learning techniques for cooperative spectrum sensing in cognitive radio networks.
Wang et al.[26]	Cooperative deep spectrum sensing in a cognitive radio network.	Convolutional neural network (CNN).	Cooperative spectrum sensing based on convolutional neural networks.

In real time (less than 10 milliseconds), artificial intelligence (AI) is essential to optimizing wireless network performance. Several of these investigations have focused on improving the efficiency and caliber of service in wireless systems through access and resource utilization. Another assumption relates to how deep learning and artificial intelligence are used in wireless LAN management to provide dynamic and automated optimization.

Finally, a notable application of artificial intelligence is the optimization of wireless network management programs through the use of techniques such as neural networks and genetic algorithms.

Table 2. Studies using model-based artificial intelligence techniques to optimize the performance of wireless networks in near real-time, between 10 ms to 1000 ms, and in non-real time over 1000 ms.

Author	**Information system approach**	**Artificial Intelligence Technique**	**The purpose of the study**
Ahmed et al.[27]	Allocation of radio resources in 5G and B5G multicellular networks.	Deep learning	Deep learning for radio resource allocation in multi-cell networks
Ghadimi et al.[28]	Optimizing radio transmission power and user data rates in wireless systems. Near real-time RIC resource allocation.	learning reinforcement learning techniques .	A reinforcement learning approach for power control and rate adaptation in cellular networks.
Sun et al.[29]	Resource allocation in signal processing.	Deep Neural Network (DNN)	Learning to Optimize: Training Deep Neural Networks for Interference Management
Challita et al.[30]	Long-term evolution (LTE) cellular communications in spectrum.	Deep learning to build predictive models on spectrum availability	Proactively manage resources for the LTE network in unlicensed spectrum.

		for distributed dynamic allocation.	
Bonati et al.[31]	Disaggregated network architecture proposed by the O-RAN Alliance as a key enabler of NextG networks.	Deep reinforcement learning.	Intelligence and learning in O-RAN for data-driven NextG cellular networks.
Zhou et al.[32]	Coordination of signal path loss in the millimeter wave (mmWave) band.	Deep learning: Deep neural network.	Interference coordination in dense millimeter wave networks.
Li et al.[33]	Radio access network and network segmentation in the RAN, TN and CN domains in an end-to-end (E2E) network segmentation system.	Machine learning for end-to-end network segmentation.	End-to-end network segmentation into radio access network, transport network and core network domains.
Abbas et al.[34]	Control, manage and monitor resources correctly based on fifth generation mobile network segmentation.	Deep learning model, the generative adversarial neural network (GAN), for managing network resources.	Segmentation of core network and radio access network domains via intent-based networking for 5G networks.
Zappone et al.[35]	Wireless communication networks in cell phones given the density of base stations.	Deep learning based on artificial neural networks.	Wireless network design in the era of deep learning.
Hammouti et al.[36]	Coverage in random wireless networks using stochastic geometry.	Neural network-based prediction of coverage probability given base station density, propagation path loss, and correlation model.	A machine learning approach to predict coverage in random wireless networks.
Mulvey et al.[37]	Detection and compensation of faults in cellular networks from an operational perspective.	Supervised learning.	Cell failure management using machine learning techniques.

Artificial intelligence is used to optimize wireless networks in non-real time (more than 1000 milliseconds). In these circumstances, artificial intelligence can examine past data and usage patterns to discover trends and optimize network design for better future performance. Another point to consider is the importance of artificial intelligence to optimize wireless network performance, particularly in real time (between 10 milliseconds and 1000 milliseconds). Artificial intelligence models, such as neural networks, are used to understand complicated patterns in data and make network configuration decisions. Genetic algorithms are used to find the best solutions for challenging optimization problems. Reinforcement learning is used to teach artificial intelligence algorithms for decision-making in dynamic contexts. These models are capable of performing real-time data analysis and making decisions to modify the network design and increase efficiency and quality of service.

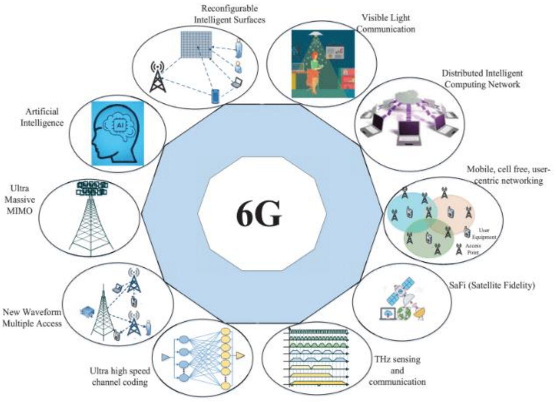

Fig. 1. Evolution of wireless communication network technologies to the sixth generation (6G).

Source: Misbah et al.[38]

The diagram in Figure 1 represents the interactions between the technologies of the 6G wireless communication network. This enables the descriptive establishment of interconnectivity between various technologies, such as artificial intelligence, RIS, photonics and VLC, DICN, cellless mobile and user-centric networks, ultra-high-speed channel coding, terahertz sensing and communication, multiple access to new waveforms, and ultramassive MIMO.

Ultimately, artificial intelligence models can evaluate data in real time and make decisions that improve access, performance, and resource use in wireless networks, which are becoming increasingly sophisticated beyond the capacity of traditional engineering. Additionally, these models can make judgments about long-term performance improvements by analyzing past data and trends to forecast future network activity.

Table 3. Studies that use model-based artificial intelligence techniques to optimize security in wireless networks.

Author	Information system approach	Artificial intelligence technique	The purpose of the study
Mohamed H. and Mohammed A. [39]	Security in wireless sensor networks using a hybrid feature reduction technique.	Excess Synthetic Minority Technique. Neural network algorithm based on deep learning.	Improve the security of wireless sensor networks (WSN) by identifying and preventing cyberattacks.
Bo Huang et al. [40]	Security of wireless network transmission data.	Machine learning with improved naive Bayesian kernel (INBK) estimation.	Prediction and security risk assessment of wireless network data transmission based on machine learning.
Misbah et al. [38]	Technological impact of the 6G sixth generation communications network.	The Sixth Generation Wireless Communication Network enables the specifications of artificial intelligence, specifically deep learning.	Evolution of technology in wireless networks of the future.
Sidra et al. [41]	Detect cyberattacks on a variety of network traffic flows.	Convolutional neural networks (CNN), and recurrent neural networks (RNN).	Evaluation of deep learning variants for cyberattack detection and multiclass classification in IoT networks.
Saida et al.[42]	Anomaly detection in IoT (Internet of Things) networks.	Machine learning and deep learning.	Machine Learning and Deep Learning Techniques for Anomaly Detection in Internet of Things Network
Shaobo et al. [43]	Distributed fiber optic sensing (DFOS) technologies.	Neural networks, convolutional types (ConvNets) and vision transformers (ViT).	Deep learning-based intrusion detection and impulsive event classification for distributed acoustic detection in telecommunication networks.
Ciric et al. [44]	Modular architecture for detecting intrusions (cyberattacks) in communication networks.	Deep learning.	Design and implement a modular network intrusion detection architecture capable of simulating cyberattacks based on real-world scenarios.
Yesodha et al.[45]	Wireless sensor network (WSN) communication.	Learning (DL) Methods: Artificial bee colony (ABC) optimization algorithm with convolutional neural network (CNN) optimized with (FT-ABC-CNN).	The intrusion detection system with CNN and the optimization of artificial bee colonies in wireless sensor networks.

According to these scientific contributions, artificial intelligence (AI) represents a key component in optimizing the security of wireless networks. It is often used to analyze large data sets using artificial intelligence base models to find trends and anomalies, allowing for proactive threat detection and prevention. Artificial intelligence is used to optimize wireless network performance, access, and resource usage. This results in effective traffic control, prioritizing important applications, and improving the user experience. This makes it possible to combine effective information system security with the full power of artificial intelligence to improve risk management, virus prevention, and intrusion detection.

Regarding aspects based on optimizing security in wireless networks, the operation of machine learning systems can face challenges due to the large amount of data required and the complex nature of the training procedure. Clearly, the scientific contributions to studies during the year 2024 are significant (Figure 2).

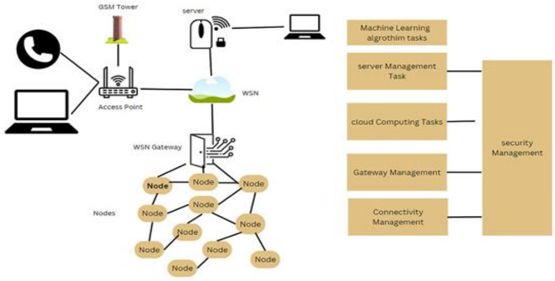

Fig. 2. General operation of algorithms in machine learning for wireless network security.

Source: Yazeed et al. [46]

In communications systems, machine learning methods such as secure multi-party computing and federated learning can be integrated into component processes to preserve data privacy and benefit from cooperative security analysis.

According to extensive reviews [46], machine learning algorithms excel at detecting patterns and anomalies in data. By exploiting programmability, machine learning-based anomaly detection techniques can be effortlessly incorporated into the network, enabling rapid detection of strange activity and potential security breaches. In this context, when machine learning techniques are used to optimize the security architecture, the network can successfully handle a greater number of nodes and data flows, allowing for the development and expansion of resources. The centralized controller can use machine learning-based security algorithms to consolidate decision-making processes, resulting in more efficient real-time threat detection and response. While improvements in machine learning approaches have made it easier to discover weaknesses and strengthen nodes' defenses against attacks, more study and analysis are required. When power or processing capacity is insufficient, this wireless network has problems [47].

Machine learning algorithms have limitations in adequately predicting future events because they learn from past data. These programs can increase task performance by obtaining new information [48]. Therefore, it is necessary to establish a greater number of facts as well as determine the additional effort required by the machine learning algorithm in light of the limited resources available in the context of wireless networks. To address this trade-off, machine learning techniques must be applied system-wide. Therefore, it can be argued that these tactics pose a direct risk to wireless network infrastructures [49]. Assuming there may be particular challenges when using these strategies in information security domains such as authentication and data integrity [50].

Below is a comprehensive analysis of current research and anticipated developments in the telecommunications industry regarding the use of artificial intelligence, machine learning, and data analytics in 5G communication networks at the edge levels, core, and RAN.

3.2. Data analysis and artificial intelligence with machine learning in 3GPP mobile networks

Data analytics and artificial intelligence/machine learning (AI/ML) in the context of 3GPP have been critical for mobile network operators (MNOs). Traditionally, MNOs have relied on collecting subscriber data, such as location, data rate, and call drops, to size and plan the network. Real-time monitoring of network failures has also been a crucial part of the operator's investment model, as it can improve anomaly detection and trigger proactive maintenance at reduced costs [51].

With the advent of smartphones, truly diversified services (data and voice) were seen for the first time, creating much more complicated data traffic patterns and forcing the adoption of data analytics for network management and optimization. However, until now, data analysis to improve network performance has been primarily diagnostic and descriptive, or has simply consisted of measuring various KPIs in different locations, which is not optimal.

In 5G and beyond (B5G) networks, not only the services offered are heterogeneous, but also the end devices. For example, the low-power Internet of Things (IoT) has very different communication requirements and hardware limitations than autonomous vehicles [52]. [53] This makes E2E optimization and optimal allocation of network segments an arduous task with added complexity that must be resolved in real time, reinforcing the need for big data analytics [51].

Proactivity over reactivity would greatly benefit mobile network operators in various events, such as possible dynamic and sudden load changes (e.g., group mobility), upcoming events in outages due to high interference in certain areas, network failures, and maintenance. This amplifies the need to move from diagnostic and descriptive analytics to predictive analytics with an associated level of confidence and data-driven control to achieve network optimization (Figure 3).

Fig. 3. *Data-driven control and optimization of high-capacity shared network*.

Fountain: Kibria et al.[51]

In essence, data analysis and its applications in the control and optimization of next-generation wireless communications systems. Systematic exploitation of big data greatly helps in making the system intelligent and facilitates efficient and cost-effective operation and optimization.

Data-centric AI is a new paradigm that highlights the importance of continuously updating data at scale to create successful and efficient AI-based information systems. This unique paradigm adds to current model-centric AI, which focuses on increasing the performance of AI-based systems by changing the model using a fixed set of data [54].

3.3. Implementation of artificial intelligence with machine learning according to telecommunications industry standards

The initial rollout of 5G focused on improving mobile broadband (eMBB) connectivity, but the full potential of 5G and beyond lies in supporting services with lower latency and higher capacity for devices (UE) per area. Two new use cases, ultra-reliable and low-latency communications (uRLLC) and massive machine-type communications (mMCC), open opportunities in various sectors such as healthcare, manufacturing, automotive, ports, and retail [55].

Mobile edge computing and network slicing are key enablers in delivering personalized services to these sectors. For example, British Telecom has managed to increase its revenue by 30% and reduce operating expenses by 40% by using a single physical infrastructure with network segmentation instead of developing separate physical networks for different services. With complete network slicing into a standalone 5G network, you can have more granular control over network resources, allowing portions of capacity to be offered to verticals and individual customers for short periods of time. This also impacts RAN orchestration, allowing for better overall performance [55]. The complexity of such a system requires comprehensive automation in different geographic areas.

3.4. Federated learning

A distributed machine learning approach known as federated learning allows you to train artificial intelligence models on multiple servers or devices without having to exchange the original data. The global model, which is returned to be trained with data that must be managed under the principle of privacy, is a crucial requirement to maintain security and privacy. Until a convergence constraint is satisfied, this process is repeated recursively. Google pioneered federated learning, which has demonstrated impressive performance in word prediction. It is not the same as other distributed learning techniques, such as split learning, where clients with low processing power train only the initial layers in DNN deep neural networks and forward the features that are recovered to a gateway or cloud for finalization the computationally intensive part of the training process.

This type of learning works very closely with the centralized baseline technique and is used to anticipate popular video material for edge caching. The different functions at the 5G core network level can be seen as learners that collect information and locally train machine learning models on certain analytical events, such as mobility, communication, and EU management.

In this regard, the study [56] investigated the idea of federated learning in a wireless access network (RAN), where a gNB base node serves as a server and the end users are represented by the user equipment. The gNB optimizes the allocation of radio resources to a subset of user equipment that is experiencing favorable channel conditions to reduce errors in the received model parameters. Analog transfers of model parameters from end devices to the server could also be useful in the context of federated learning in the RAN. By using all available bandwidth to connect to the server, any end device in the analog world can contribute to model updates, thus decreasing the time required for the model to converge [57].

It is crucial to understand that in federated learning, the server does not care about the individual parameters calculated by each end device but rather the total sum of these parameters, which is comparable to the superposition of the analog signals received at the server. For more details on federated learning in the context of Mobile Edge Computing (MEC), see [58], while [59] discusses open research problems and possible future paths. For federated learning in 6G communication networks.

4. Discussion

The field of artificial intelligence (AI) has recently seen a lot of upheaval, with the advent of fundamental models as a new paradigm for the development of artificial intelligence systems [60]. Base models are large-scale AI models that have been pre-trained using a significant amount of generic data and can be fine-tuned for future applications. This method of pre-training and adaptation accelerates the creation of new AI-based products and services, as well as the availability of high-performance artificial intelligence solutions in a variety of sectors [61].

Basic models have impressive capabilities for understanding, producing, and modifying material in a variety of domains: software debugging [62], creative generation [63], [47], and cross-modal outputs such as text-to-image developments [64]. The range of applications that a single model can perform without the need for more training data or adjustments increases with scaling, making basic models increasingly better suited to perform tasks for which they were not specifically trained [65]. When necessary, rapid or efficient engineering methods can be used to further improve the performance of specific tasks. Both have much lower costs than creating a new model from scratch. [67]

Core models bring about a paradigm shift that changes the way AI applications are designed and implemented. These large-scale basic models, including their newly developed capabilities, promote industry convergence in artificial intelligence, resulting in an increasing number of proprietary modifications of a small number of basic models that are used in applications of artificial intelligence in a few companies and trained using a limited number of data sets [60].

This standardization has significant potential to drive advances in artificial intelligence in various fields. However, it also raises issues including economic linkages, monopoly power arrangements, and the potential propagation of weaknesses in model construction into various downstream applications [68]. The dynamics of value creation and accumulation in the AI industry can be expected to change as core models become established as the cornerstone of cutting-edge AI advancement. In an era where high-performance, cross-functional AI solutions are widely available, organizations may be forced to reconsider how they can differentiate their AI products and services. Finally, the move from fragmented models to a fundamental approach challenges current AI governance techniques as the design and control of artificial intelligence systems are distributed across an increasingly contributing [69] ecosystem. [70]

The emergence of core models will influence the direction of research for AI developments by changing preconceived notions about development, management, and governance promoted by machine learning algorithms. This will present important challenges and possibilities for the area of research in computer science, business and information systems engineering, and information technology [56], [61], and [71]. In addition to outlining a socio-technical point of view [2] on the complex ramifications of this new paradigm for the development and implementation of artificial intelligence systems, our objective with this short article was to deepen our knowledge of the fundamental concepts on the subject and the recent contributions.

5. Gaps in research

In certain areas, research is still lacking on the application of artificial intelligence and data analysis to improve the security and performance of information systems. These include the absence of guidelines for assessing the security of AI-powered systems, the requirement to create more reliable techniques for identifying anomalies, and the scarcity of high-quality data for training AI models. In addition to being able to handle the moral dilemmas posed by the increasing autonomy of AI systems, which raises concerns about liability for errors or mishaps,

6. Conclusions

The traditional approach to improving the performance of wireless transceivers is based on dividing the transceiver into signal processing blocks that perform functions such as channel equalization, demodulation, and error correction. However, the simplicity and manageability of the transceiver are compromised by this limited focus. As a result, research has been conducted using artificial intelligence methods to improve wireless network performance instantly, paying special attention to deep learning, radio resource allocation, and interference management. Additionally, artificial intelligence is used to examine historical data and user behavior to optimize network architecture and improve performance in the future.

Communication system optimization is necessary to meet various technological requirements efficiently, and AI-based network orchestration using machine learning is essential. Dynamic resource management is necessary since it is wasteful to implement dedicated networks in each sector. The main tools to optimize current and future networks are machine learning, artificial intelligence, network monitoring, and data collection.

Current topics of interest focus on creating methods for deep learning systems to explain their suggestions and use the benefits of deep learning to increase performance with less pre-processing code. Future studies in this area will be guided by the evolution of mobile network architecture and characteristics, as well as the difficulties in using machine learning techniques in an operational environment. The development of network design has given rise to new areas of research in data storage, edge computing, virtualization, and network complexity management. Limiting the exploratory behavior of active machine learning systems in an active network and increasing awareness of contextual issues are some of the research challenges.

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