Review on Artificial Intelligence Application for Enhancing Path Loss for Resource Management in 5G Network

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***Abstract*: This study explores the application of Artificial Intelligence (AI) techniques like machine learning, deep learning and reinforcement learningfor enhancing path loss prediction accuracy for network resource management in 5G networks. Through a comprehensive literature review and conceptual analysis, the study highlights the strengths and limitations of various AI models such as Support Vector Regression (SVR), Random Forest (RF), Convolutional Neural Networks (CNN), and hybrid models combining techniques like Principal Component Analysis (PCA) and Gaussian Processes (GP). These models demonstrate improved performance in learning nonlinear propagation patterns, adapting to environmental variability, and optimizing network design parameters such as base station placement and interference mitigation. Ultimately, this research underscores the transformative potential of AI-driven methods in revolutionizing path loss prediction and network optimization in 5G and future wireless communication systems, while also identifying key challenges and directions for future research. Finally, the work recommends that future studies should aim at developing lightweight and interpretable AI models, incorporating transfer learning to overcome data scarcity and expanding the range of training datasets to improve model robustness.**

***Keywords*: Path Loss; 5G Network; Resource Management; Artificial Intelligence; Machine Learning.**

1. Introduction

Cellular network technology continues to advance in infrastructure and user base, leading to an increased demand for mobile data traffic. To address this rising demand, researchers are exploring higher frequency bands above 6 GHz, aiming to meet user requirements for enhanced quality of service. This shift is driven by the necessity to support the growing number of connected devices and the need for faster, more reliable mobile connectivity in various applications, including IoT and streaming services (Iliev et al., 2024).

Cellular networks are made of multiple base stations, each equipped to measure the signal strength from neighboring base stations and receive or transmit packets via radiowave (Kwon and Son, 2024). During the data transmission, several factors, such as pathloss, affect the quality of signal propagation. Pathloss is a phenomenon in which the radio signal strength between the transmitting base station and the receiver mobile station is diverse as it propagates through space (Loh et al., 2023). This path loss usually increases as the distance between the receiver and transmitter increases (Kwon and Son, 2024). Other factors that can influence pathloss include antenna elevation, frequency, and environmental factors such as attenuation, reflection, snow, and scattering particles (Valentine et al., 2021).

According to Nguyen et al. (2021), pathloss models play a vital role in the optimization of base station performance and have been applied in several areas, which include cell deployment, resource management, link budget, cell estimation, congestion control, and coverage area prediction. Kwon and Son (2024) classify these models into two categories: empirical and deterministic models. The former are models obtained based on a given range of frequency in a specific environment, while the latter make use of physical laws governing the propagation of radio-waves to predict transmission loss at a particular location. It requires less computation effort, is easy to use, and is less expensive to apply, unlike the deterministic, which is site-specific (Bidikar et al., 2020; Gonzalez et al., 2021; Sokunbi et al., 2021).

In the context of pathloss, ML algorithms such as support vector machine, k-nearest neighbors, random forests, and artificial neural networks (Kwon and Son, 2024) have all been applied for pathloss prediction purposes and have recorded success in correctly characterizing environmental conditions; however, Elmezughi et al. (2022) argued that these models are all limited to the environment where their training data were collected. This means that the existing models cannot be generalized to all environments. Secondly, models with high prediction accuracy are rare in literature, and finally, to the best of our knowledge, existing models are limited to single frequency bands. Therefore, this paperreviews the use of machine learning-based path loss prediction model that takes into consideration these challenges to make predictions. This prediction will form the foundation for a resources management model that will ensure adaptive allocation of resources based on current network conditions, thereby maintaining quality of service and network efficiency. Overall, the convergence of the proposed ML based pathloss prediction models and dynamic resource management will provide intelligent and efficient wireless communication systems, which will help meet the growing demand for high-quality connectivity, and quality of user experience in wireless network designs. The contributions of the study highlights that:

i. The work comprehensively explores the application of AI-techniques for path loss management in 5G network environment. This brings together the diverse AI approaches for accurate path loss management in 5G wireless communication network
ii. Reviewed various research works conducted on path loss and resource management, focused on the techniques applied, strengths and limitations of the technique in terms of path loss and resource management
iii. Conceptually discussed the concept of path loss and resource management. Identified different techniques that are applied for their effective implementation and the challenges in resource management
iv. Propose a research direction for future studies towards ensuring path loss and resource management efficiency

2. Literature Reviews

Over the years, several studies have been conducted of pathloss prediction using different techniques, with machine learning approach dominating recent literatures. This section presents some of the related work, considering their techniques, methods, data used and results obtained.

Kwon and Son (2024). Accurate Path Loss Prediction Using a Neural Network Ensemble Method. The study proposed the application of artificial neural network-based ensemble model for the prediction of pathloss in 5G network. The dataset used was collected from Covenant University considering parameters such as longitude, latitude, elevation, altitude, cluster and distance between transmitter and receiver, across three different routes. Different numbers of neural networks were trained experimentally from 4 to 40 and comparatively analyzed. The ensemble model with 20 neural networks recorded the best which are MSE value of 8.6529, RMSE reported 2.9416, MAE reported 1.2753, MAPE recorded 0.0090, MSLE reported 0.0004, RMSLE recorded 0.0210 and R^2 reported 0.895.

Iliev et al. (2024). A Machine Learning Approach for Path Loss Prediction Using Combination of Regression and Classification Models.The study consists of two regression models and one classifier. The first regression model is adequate when a line-of-sight scenario is fulfilled in radio wave propagation, whereas the second one is appropriate for non-line-of-sight conditions. The classification model is intended to provide a probabilistic output, through which the outputs of the regression models are combined. The number of used input parameters is only five. They are related to the distance, the antenna heights, and the statistics of the terrain profile and line-of-sight obstacles. The proposed approach allows creation of a generalized model that is valid for various types of areas and terrains, different antenna heights and line-of-sight and non line-of-sight propagation conditions. An experimental dataset is provided by measurements for a variety of relief types (flat, hilly, mountain, and foothill) and for rural, urban, and suburban areas. The experimental results show excellent performances in terms of a root mean square error of a prediction as low as 7.37.3 dB and a coefficient of determination as high as 0.702.

Ojo et al. (2022). Path Loss Modelling: A Machine Learning Based Approach Using Support Vector Regression and Radial Basis Function Models.The study proposes Support Vector Regression (SVR) and Radial Basis Function (RBF) models for path loss predictions in rural, suburban, and urban areas. The following environmental input parameters are used: elevation; clutter heights; distance; altitude; building-to-building distance; the street orientation angle; and base station antenna heights (fixed to 25 mm and 35 mm). The obtained $RMSE$ values for the three types of areas are 1.3781.378 dB; 1.4521.452 dB; and 2.1572.157 dB. The results show a very good regression fitting because the measured points are located approximately on three straight lines originating at the base station. Unfortunately, we did not find any information about the operating frequency.

Jo et al. (2020). Path Loss Prediction Based on Machine Learning Techniques: Principal Component Analysis, Artificial Neural Network, and Gaussian Process. A technique that combines Artificial Neural Networks (ANNs) with Gaussian process (GP) variance analysis and principal component analysis is proposed. The multi-layer perceptron (MLP) is the core of the ANN architecture. The input parameters of the model are frequencies (450 MHz, 1450 MHz, and 2300 MHz); elevation plus transmitting antenna height; elevation plus receiving antenna height; and the difference between these two heights. The data are collected for only one transmitting antenna height (15 mm) and for suburban propagation conditions (small town). The achieved quantities for the regression performance using the ANN for frequency 450 MHz are as follows: $RMSE$=7.876dB; MAE=5.896dB; and R^2=0.3975.

George and Idogho (2022). Path loss prediction based on machine learning techniques: Support vector machine, artificial neural network, and multi linear regression model. Three ML regression models are investigated and compared; ANN; support vector machine; and multi-linear regression. The measurements are made for one frequency (900 MHz) and one transmitter antenna height (100 mm). The communication distance is limited within the range 100 mm to 800 mm, and a very few number of geographical points (<100) are considered. We believe this is the reason for the very good approximation results that are reported ($RMSE$ = 0.008438 and R^2 = 0.999675) when using ANNs.

Elmezughi et al. (2023). Path loss modelling based on neural networks and ensemble method for future wireless networks. An ensemble method consisting of three neural network models which are conventional ANNs, long short-term memory-based recurrent neural networks, and convolutional neural networks wasanalysed. The prediction of path loss is for an indoor environment at three frequencies of 14 GHz, 18 GHz, and 22 GHz. The data used in this research are collected in an indoor environment for line-of-sight (LOS) and non-line-of-sight (NLOS) scenarios. The input features are distance; frequency; angle of arrival; and transmitter antenna height. The distance ranges from 2 to 24 mm. Measurements at various frequencies are carried out for 865 points. The studied models demonstrate high accuracy in terms of the maximum value of $RMSE$ being less than 0.31620.3162 dB and the average value of R^2 being as high as 0.9753

Mughal et al. (2024). Resource management in multi-heterogeneous cluster networks using intelligent intra-clustered federated learning. The study was on the use of intelligent Intra-Clustered Federated Learning (ICFL) technique for resource management in heterogenous cluster network. Federated Learning (FL) was employed as the methodology to enable several heterogeneous cluster networks through the usage of ICFL. For the node cluster, ICFL maximise connectivity and computation. Sensitive asynchronous data was protected from potential misuse while adjusting to changing circumstances using ICFL. Node selection while data transfers between nodes are carried out safely and anonymously. The system uses several categorisation factors at the Heterogeneous Cluster Network (HCN), Cluster, and CFS levels to make their relationship to FL-enabled HCNs and the Internet of Things (IoTs) clearer. The ICFL resulted in a 62% reduction in training rounds and a 6.5% increase in accuracy after rigorous testing. Compared to current models, it can complete assessments 7.46 times faster, and its average accuracy has increased by 4.39%.

Li et al. (2023). Multi-agent deep reinforcement learning based resource management in SWIPT enabled cellular networks with H2H/M2M co-existence. Ad Hoc Networks. This study looked at the resource management issue in cellular networks where H2H and M2M coexist. The study first took into account the energy-constrained nature of Machine Type Communication Devices (MTCDs), after which it suggested a unique network architecture made possible by SWIPT, giving MTCDs the capacity to carry out information decoding and energy harvesting (EH) at the same time. Considering the wide range of features included in IoT devices. The work then created a multi-agent DRL-based plan to address this issue. It offers the best allocation rules for spectrum; transmit power, and Power Splitting (PS) ratios. It also facilitates effective model training in a state space with a shared reward function and behaviour-tracking architecture. In the future, user mobility will be considered and a centralised method that can offer dynamic resource allocation for various user types in an H2H/M2M coexistence network will be developed; this scheme will be more appropriate for real-world communication scenarios.

Hassan et al. (2024). The management of radio resources for hybrid energy cellular networks that has battery constraints using reinforcement learning. This study examined the Smart Grid and cellular networks that are battery-operated and fuelled by renewable energy sources. Next, taking into account the fluctuating cost of grid energy, traffic fluctuations, and the production of renewable energy, reinforcement learning was taken into consideration to minimise grid energy costs and maximise user happiness. Unlike previous research, this study accounts for user variability as well as battery depreciation. A Q-learning technique is also proposed in this study to determine the optimal amount of active radio resources, taking into account two scenarios: one with and one without battery limitations.The simulation results emphasise the significance of

Table 1
Summary of literature

Author	Technique	Strengths	Weaknesses
Kwon and Son (2024)	ANN-based ensemble (20 NNs)	High accuracy (R^2 = 0.895) Diverse route data	Computational cost increases with more networks
Iliev et al. (2024)	Combination of classification and regression models	Handles LOS and NLOS Generalizable across terrains	R^2 = 0.702 is moderate Lacks frequency variation
Ojo et al. (2022)	SVR and RBF models	Accurate RMSE (1.378–2.157 dB) Good generalization across environments	No frequency info Fixed antenna heights
Jo et al. (2020)	PCA + ANN (MLP) + GP	Combines dimensionality reduction with probabilistic estimation	Low R^2 = 0.3975 Limited to 1 antenna height and suburban data
George and Idogho (2022)	ANN, SVM, MLR	Extremely high R^2 (0.999675); RMSE = 0.008438	Very small dataset Limited coverage (short range, <100 points)
Elmezughi et al. (2023)	Ensemble of ANN, LSTM, CNN	High accuracy (RMSE < 0.3162) Tested across LOS/NLOS and 3 frequencies	Indoor only Distance range is narrow (2–24 mm)
Mughal et al. (2024)	Intra-Clustered Federated Learning (ICFL)	Improves speed (7.46x faster), accuracy (+4.39%) Preserves data privacy	Complex setup Indirect link to path loss modelling
Li et al. (2023)	Multi-agent Deep RL in SWIPT systems	Efficient spectrum & power allocation	Focuses more on resource management than path loss prediction
Hassan et al. (2024)	Q-learning in hybrid energy networks	Considers battery depreciation Grid energy cost reduction	Long-term validation needed Limited to energy-focused networks
Boutiba et al. (2023)	MILP + Deep RL Scheduler in 5G NR	Scalable to large bandwidths Supports dynamic user loads	Relies on prior MILP setup Specific to network slicing context

placing limitations on battery operation. They also report that a year later, system investigation revealed that the loss was justified because, with battery constraints taken into account, both system performance and battery health will improve over time.

Boutiba et al. (2023). Optimal radio resource management in 5G Network Radio (NR) featuring network slicing. Computer Networks. The paper models radio resource management in 5G NR using a Mixed Integer Linear Program (MILP) and network slicing approaches. The methodology utilised resources allocated per User Equipment (UE) throughout a time window that considers the UE's channel quality to train Deep Reinforcement Learning (DRL) as a scheduler. The DRL scheduler was made to function regardless of how many users there are on the systems. Scalable for large bandwidths spanning both FR1 and FR2 frequency bands with bandwidths up to 400MHz, the DRL state was simulated and the results recorded a successful network resource management to avoid congestion. This summary of the reviews are presented in Table 1, where the strengths and weaknesses of the techniques adopted by various researchers are pointed out.

3. Concept of Path Loss Prediction in 5g

Path loss prediction is a fundamental concept in the design and optimization of 5G networks. Path loss refers to the reduction in signal power as it propagates through space and interacts with obstacles, such as buildings, trees, and atmospheric conditions (Adegoke et al., 2020). Accurate prediction of path loss is crucial for ensuring reliable connectivity, optimizing network coverage, and minimizing interference in 5G networks. Given the higher frequency bands used in 5G, such as millimeter waves (mmWave), path loss becomes more significant due to increased susceptibility to attenuation and scattering (Idogho and George, 2022).

Several factors influence path loss in 5G, including frequency, distance, environment, and propagation conditions (Aldossari, 2023). High-frequency signals used in 5G, like mmWave, experience greater free-space path loss compared to lower-frequency signals due to their shorter wavelengths (Kharwal, 2023). Environmental factors, such as urban density, building materials, and vegetation, also significantly affect signal propagation. Non-line-of-sight (NLOS) conditions, where the direct path between the transmitter and receiver is obstructed, can further increase path loss. Additionally, weather conditions, such as rain and humidity, can lead to signal degradation, especially in higher-frequency bands (Kharwal, 2023; Phaiboon and Phokharatkul, 2020).

To account for these factors, various path loss models are used in 5G network planning and deployment. Standard models, such as the Okumura-Hata model, COST-231 model, and ITU-R models, are often extended or adapted for higher frequencies (Saba et al., 2021). Additionally, site-specific models like ray-tracing simulations provide detailed insights by considering precise environmental layouts. 5G-specific models, such as the 3GPP TR 38.901 model, are designed to predict path loss in diverse scenarios, including urban macro (UMa), urban micro (UMi), and indoor environments, ensuring compatibility with 5G's unique propagation characteristics (Daho et al., 2021).

Path loss prediction plays a vital role in multiple aspects of 5G network design. It helps in determining the optimal placement of base stations, small cells, and repeaters to maximize coverage and capacity (Juan-Lláceret al., 2022). Accurate path loss modelling ensures effective beamforming and massive MIMO (multiple-input, multiple-output) configurations, which are key features in 5G for enhancing spectral efficiency (Bedda-Zekri and Ajgou, 2022). Additionally, it supports efficient handover strategies, interference management, and power control mechanisms, ensuring seamless connectivity and quality of service (QoS) for users in 5G networks architecture shown in Figure 1.

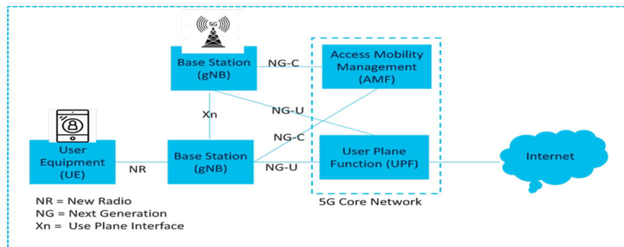

Fig. 1. Simple architecture of 5G network (rayes and denopoli, 2021)

A. *Artificial Intelligence (AI) for Path Loss Prediction*

Artificial intelligence (AI) has revolutionized path loss prediction in 5G networks by providing tools that deliver enhanced accuracy, adaptability, and computational efficiency over traditional mathematical models (Wang et al., 2021). Path loss, a critical factor in wireless network planning and optimization, involves the reduction of signal strength as it propagates through the environment. Unlike classical models that rely on fixed mathematical formulations and simplified assumptions, AI techniques utilize data-driven methodologies to analyze signal attenuation in complex, real-world conditions (Chen et al., 2021). By integrating parameters such as terrain types, frequency ranges, building materials, and weather conditions, AI models can learn intricate propagation patterns from large datasets (Vergos et al., 2021). These capabilities enable AI to address the limitations of conventional approaches, especially in heterogeneous and dynamic 5G network scenarios, where propagation characteristics vary significantly across different locations and conditions.

1) *Machine Learning Models for Path Loss Prediction*

Machine learning (ML) techniques, such as decision trees, support vector machines (SVM), and random forests, are widely applied for path loss prediction. These algorithms process datasets containing critical environmental features such as geographical terrain, urban density, and obstacles, alongside network-specific parameters like frequency and antenna configurations (Sasaki et al., 2021). Trained on this diverse data, ML models can make accurate path loss predictions even in non-linear and highly complex environments. For instance, random forests excel in handling noisy data and identifying non-linear interactions, while SVMs are effective in environments with high-dimensional input variables. These ML models provide scalable and computationally efficient solutions for real-world 5G scenarios (Shaibu et al., 2023).

2) Deep Learning Approaches for Path Loss Prediction

Deep learning (DL) models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), offer significant advancements in path loss prediction by capturing both spatial and temporal dependencies (Sotiroudis et al., 2021). CNNs are adept at processing spatial data, such as geographical layouts and environmental features, identifying patterns related to signal propagation across varying terrains (Shaibu et al., 2023). RNNs, on the other hand, are well-suited for modelling time-dependent variations in path loss, such as those caused by changing weather or user mobility (Juang et al., 2021). Hybrid architectures like CNN-LSTM further enhance prediction accuracy by combining the strengths of CNNs in spatial analysis with LSTMs' ability to model sequential data (Sasaki et al., 2021). These models are particularly beneficial in urban environments where complex structures and high mobility create dynamic signal propagation challenges.

3) Reinforcement Learning for Path Loss Prediction

Reinforcement learning (RL) takes a unique approach to path loss prediction by employing trial-and-error learning from real-time feedback. Unlike supervised models, RL systems learn optimal prediction strategies by interacting with the environment and adapting their parameters to minimize prediction errors (Shaibu et al., 2023). This adaptability makes RL particularly effective in dynamic network scenarios, such as vehicular communications and drone-assisted networks, where mobility and environmental changes significantly impact signal propagation. By continuously optimizing prediction accuracy, RL ensures efficient resource allocation and reliable network performance in fast-changing 5G environments.

4) Hybrid AI Models for Path Loss Prediction

Hybrid AI models integrate multiple AI techniques to create robust and scalable path loss prediction frameworks. For instance, combining ML algorithms with optimization methods like genetic algorithms or particle swarm optimization enhances the adaptability of prediction models (Sotiroudis et al., 2021). Similarly, hybrid architectures that merge DL with RL can leverage both historical data and real-time learning to optimize predictions across diverse propagation scenarios (Kim et al., 2022). These hybrid approaches are particularly valuable in 5G networks, where varying frequencies (such as sub-6 GHz and mmWave bands) and deployment settings (urban, rural, and indoor) demand flexible and comprehensive prediction mechanisms.

B. Overview of Resource Management in 5G Networks

Resource management in 5G networks plays a pivotal role in meeting the high-performance requirements of this next-generation communication technology. With its ability to support a wide range of applications, including enhanced mobile broadband (eMBB), ultra-reliable low-latency communication (URLLC), and massive machine-type communication (mMTC), 5G introduces unprecedented complexity in resource allocation (Kuno et al., 2021). These diverse use cases demand a holistic approach to managing spectrum, energy, and computational resources to ensure efficient and reliable service delivery. Effective resource management is critical to maintaining the seamless connectivity, high throughput, and low latency that define 5G networks (Ahmad and Hussain, 2022).

One of the key challenges in 5G resource management is the dynamic allocation of bandwidth to accommodate a variety of traffic types (Raj et al., 2021). Unlike traditional networks, 5G must simultaneously handle high-data-rate applications like video streaming and latency-sensitive tasks such as autonomous vehicle communication (Raie et al., 2022). The fluctuating nature of traffic loads adds another layer of complexity, requiring resource allocation strategies to be both adaptive and predictive. To address this, 5G networks leverage machine learning algorithms to analyze traffic patterns and predict resource demand in real time, ensuring optimal bandwidth utilization (Jang et al., 2022).

Another critical aspect of resource management in 5G is latency optimization for applications like URLLC. These applications, which include industrial automation, telemedicine, and augmented reality, require ultra-low latency and high reliability. To achieve this, resource management strategies focus on reducing transmission delays and ensuring that computational tasks are processed closer to the user through edge computing. Edge computing decentralizes data processing, enabling faster response times by offloading tasks from centralized cloud servers to local edge nodes. This not only reduces latency but also minimizes the burden on core network resources (Sukemi et al., 2023).

Dynamic spectrum management is another cornerstone of 5G resource allocation. 5G networks operate across multiple frequency bands, including sub-6 GHz and millimetre waves, which have vastly different propagation characteristics (Barcellos et al., 2023). Resource management strategies must dynamically allocate spectrum based on user requirements, environmental conditions, and network load. Techniques such as dynamic spectrum sharing (DSS) allow 5G to coexist with existing technologies like 4G, enabling efficient use of available frequency bands. Network slicing further enhances spectrum utilization by partitioning the network into virtual slices tailored to specific applications, ensuring dedicated resources for critical tasks without compromising overall network performance (Nguyen et al., 2023).

4. Research Findings

Dynamic urban environments: Urban environments are constantly changing due to alterations in building layouts, vegetation, and infrastructure. Existing empirical models may struggle to account for these dynamic shifts, leading to inaccuracies in path loss predictions. There is a need to integrate real-time or dynamic elements into these models to address this gap, ensuring they can handle the worst-case urban scenarios and remain reliable across various urban settings. Current models may also fail to adequately capture interference and multipath effects, further reducing their prediction accuracy.

a. *Inadequate integration of machine learning techniques*: Machine learning approaches, including random forest models and neural networks, have demonstrated potential for improving path loss prediction accuracy, particularly in mid-band and high-band frequency ranges. However, research on effectively incorporating these techniques into empirical models for path loss prediction in urban environments, specifically in mid-band frequencies, is limited. This presents a valuable research opportunity to explore how machine learning can enhance existing empirical models and improve their predictive capabilities.
b. *Inadequate consideration of complex environments*: The empirical models currently used often fail to sufficiently factor in the complexities of urban environments, such as high-rise buildings, dense vegetation, and diverse land use patterns. This leads to inaccuracies in path loss estimation. Developing models that can accurately reflect the unique characteristics of complex urban and suburban environments is an essential research gap that needs to be addressed for more accurate predictions.
c. *Lack of relevant features in labelled training data*: There is a scarcity of relevant features in labelled datasets such as distance between transmitter and receiver, frequency of transmission, antenna heights, elevation and terrain profile, clutter type and heights, time of day and environment types particularly in the context of machine learning models like ANN that have outperformed other models. This lack of essential features significantly hampers the ability to develop accurate models for path loss prediction. Addressing this gap by incorporating multiple parameters and testing the models in commercial environments with more obstructions will be crucial in assessing the models' stability and reliability.

Despite advancements in pathloss prediction models, significant gaps remain. One key gap is the need for dynamic resource allocation that accounts for user mobility. Current models, such as those by Li et al. (2023), focus on static conditions, limiting their real-world applicability in scenarios where users are frequently mobile. Another gap, identified by Kwon and Son (2024), is the reliance on public datasets for pathloss prediction models, which limits the model's adaptability across different environments. This makes it difficult to generalize predictions in diverse network conditions, further highlighting the need for models that can account for environmental variability.

5. Conclusion

This study critically examined the application of Artificial Intelligence (AI) techniques for path loss prediction in 5G networks through a comprehensive literature review focusing on machine learning, deep learning and reinforcement learning methods. The review revealed a significant shift from traditional empirical and deterministic models towards data-driven AI-based approaches which have demonstrated superior performance in terms of prediction accuracy, adaptability to dynamic environments and scalability across various 5G deployment scenarios, particularly within the high-frequency millimetre-wave bands.Machine learning models such as SVR, RF and GB have been widely adopted for path loss prediction in urban, suburban and rural settings andthe models often outperform classical models by learning complex patterns from real-world datasets. Then, DL architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have shown notable success in capturing nonlinear relationships between environmental features and signal propagation characteristics. Furthermore, reinforcement learning and federated learning approaches offer real-time adaptability and privacy-preserving capabilities, making them suitable for dynamic and decentralized network environments.

Hybrid approaches that combine different AI modelssuch as Artificial Neural Networks (ANN), Principal Component Analysis (PCA), and Gaussian Processes (GP)have also proven effective in enhancing prediction accuracy by leveraging the strengths of each technique. These models not only improve the precision of path loss estimation but also help optimize network parameters like base station placement, interference management, and beamforming, which are crucial for supporting advanced 5G functionalities such as massive MIMO. Finally, the conceptual analysis highlighted the critical role of accurate path loss prediction in ensuring optimal network performance by environmental conditions, propagation characteristics and deployment scenarios significantly affect the reliability of prediction models. Hence, the adoption of AI techniques offers a context-aware solution which is capable of adapting to these variations in real time.

In conclusion, AI-driven models present a promising alternative to conventional path loss prediction techniques in 5G networks. Challenges such as limited data availability, model interpretability, computational overhead and generalization across diverse scenarios remain active areas of research where future research can consider, then should equally aim at developing lightweight and interpretable AI models by incorporating transfer learning to overcome data scarcity. The fusion of AI with wireless communication technologies holds vast potential in shaping the next generation of smart, adaptive, and high-performance wireless networks.

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