Enhancing 5G Internet of Things (IoT) Connectivity Through Comprehensive Path Loss Modeling: A Systematic Review

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ABSTRACT
Optimizing connectivity becomes paramount as the integration of 5G networks and the Internet of Things (IoT) continues to revolutionize communication landscapes. This systematic review digs into the intricacies of path loss modeling, a critical aspect of ensuring robust 5G IoT connectivity. By synthesizing and analyzing diverse research studies, this review aims to provide a comprehensive understanding of the current state of path loss modeling in the context of 5G IoT networks. We explored emerging methodologies and technologies that contribute to the optimization of path loss modeling and ultimately paved the way for enhanced and reliable 5G IoT connectivity. The study presents a comprehensive survey of IoT connectivity in 5G networks, specifically focusing on the different path loss models utilized in designing and installing 5G network infrastructure. Our review contributes by examining the characteristics of 5G networks, detailing the architecture of IoT in the 5G network, exploring diverse path loss models employed in 5G network planning, and highlighting both current challenges and promising research areas for the future of IoT connectivity. This research aims to provide valuable insight for researchers, practitioners, and industry professionals working on optimizing 5G IoT networks.

Keywords: Connectivity, Path loss, 5G Networks, Internet of Things(IoT), Network Radio(NR)

1 INTRODUCTION

The revolution of wireless communication systems aims to meet the demands of users. The rate of data utilization has exponentially increased due to the improvement in technology. The evolution of mobile generations has progressed from the first generation (1G) to the fifth generation (5G). This trend is driven by significant technological advancements aimed at achieving optimal connectivity for devices (del Peral-Rosado et al., 2017; Kim *et al.,*2019), as illustrated in Figure 1. This connectivity is hindered by factors such as path loss, latency, and limited bandwidth. However, a significant challenge in wireless communication is the loss of signal strength as it travels through the channel, known as path loss. Path loss refers to the decrease in signal power over distance due to various factors such as distance, frequency, obstacles, and environmental conditions. Path loss models are mathematical tools used to represent this signal attenuation. Accurately understanding and modeling path loss is essential for the design and optimization of wireless communication systems, as it affects the coverage area, link quality, and overall network performance. By modeling path loss, engineers can enhance various aspects of a wireless system, such as antenna placement, transmit power control, and interference management, thereby improving the system's performance and reliability. The 4G was proposed in the early 2000s and was the first network generation that utilized an Internet Protocol (IP) packet-switching scheme (Agiwal *et al*.,2021). About a decade after the deployment of the 4G network and due to the dynamic nature of the environment, some challenges such as high latency, low speed, and interference become major factors (Agiwal *et al*.,2021).

Internet operators and users are eager for means to connect with data rates up to gigabytes per second (Gbps). The emergence of the fifth generation (5G) network in the early 2020s marks a digital society. This network integrates a new invention called the IoT (Chettri and Bera, 2019). IoT is a sophisticated technology that connects devices, people, platforms, software, and objects to the Internet (Sinche *et al.,*2019; Stoyanova *et al*.,2020). Recently CISCO industry reported that more than 500 billion devices will be connected to the Internet by 2030. These devices will be endogenously equipped with IoT modules that allow device-to-device(D2D) communications to each other, forming an IoT ecosystem. The IoT is utilized in various sectors such as smart cities An *et al.,*2019; Cirillo *et al .,*2020) smart transportation, smart agriculture, education, and healthcare systems (Neto et al.,2018; Zhu et al.,2019).

The main features of IoT applications are long-range, low data rate, low energy consumption, and cost-effectiveness. Low-power wide area networks (LPWAN) are deployed to meet these different requirements for IoT facilities. LPWANs work in both licensed and unlicensed frequency bands. Many LPWAN technologies have been examined by different standards and industrial consortia, such as LoRa, Sigfox, NB-IoT, ECGSM-IoT, Random Phase Multiple Access (RPMA), Weightless, DASH7 alliance, etc. 5G New Radio (NR) is the global standard for a new air interface developed to meet the diverse requirements of the 5G mobile communication system. The 5th generation (5G) NR system is expected to outperform LTE C-V2X, delivering superior performance in high-throughput, low-latency, and highly reliable scenarios, particularly in congested traffic conditions and across a variety of vehicular applications. It was specified by the 3rd Generation Partnership Project (3GPP), an organization that develops protocols for mobile telecommunications. The key features are enhanced mobile broadband (eMBB), ultra-reliable low-latency communication (URLLC), and Massive Machine-Type Communications (mMTC). These improve the connectivity of IoT devices and enable smart cities, smart agriculture, and other IoT applications. However, the channel connectivity is hindered by delay sensitivity caused by the effective path loss modeling approach (Ali.,*et al.,*2023)

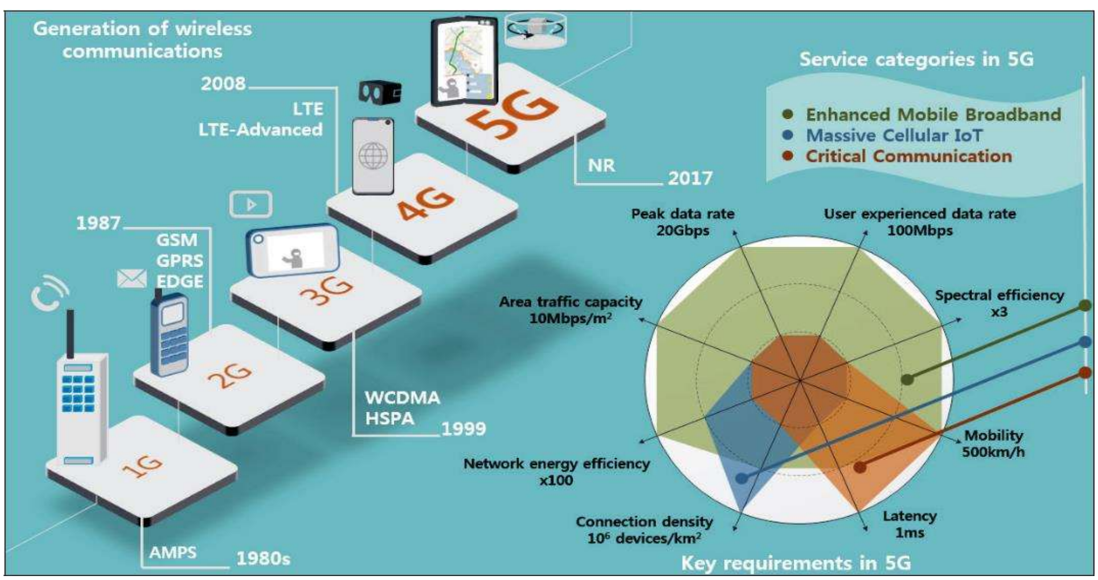

Figure 1: 5G cellular mobile Communication Requirements ITU-R(Kim *et al.,*2019)

However, the results of the studies also indicated that IoT networks in 5G have a lot of issues such as poor connectivity, quality of service (QoS), energy utilization, privacy, and security threats. Communication solutions including the design, routing algorithm, protocol, and spectrum have been proposed to solve these problems. In this study, we conduct a comprehensive survey of IoT connectivity in 5G networks to examine different path loss models used in the design and installation of 5G network equipment. Our main contributions to this study are as follows: Characteristics of the 5G network, the architecture of IoT in the 5G Network, different path loss models used for 5G network planning, and challenges and attractive research areas in the future of connectivity for IoT. This work is organized into different sections. Section one is the introduction of the study, section two is the related works and section three is the conclusion and the direction of the future studies

2. RELATED WORKS

Examining the radio propagation models is pertinent in planning, installing, configuring, and managing the 5G network spectrum. This facilitates reliable IoT connectivity and boasts user confidence in the utilization of network equipment (Samad *et al.,*2021).To achieve this, various concepts such as the characteristics of the 5G network planning, the architecture of IoT in the 5G Network, different path loss models used for 5G network planning, and challenges and attractive research areas in the future of connectivity for IoT are investigated.

2.1 Characteristics and Technical Specifications of 5G Network

Massive MIMO (Multiple Input Multiple Output): Massive MIMO, an integral technology for 5G networks, enables the simultaneous transmission and reception of multiple signals on the same radio channel. When coupled with 5G, its performance surpasses that of Wi-Fi or 4G-LTE. Enhanced spectral efficiency and coverage result from directing energy into smaller spatial regions through the use of additional antennas (Dahlman *et al.,*2016).NOMA (Non-Orthogonal Multiple Access): NOMA, a pivotal radio access technology in 5G, offers advantages such as low latency and extensive high-speed connectivity. Code domain NOMA, frequently paired with mMIMO, significantly improves spectral efficiency. Power domain NOMA exhibits versatility in its application with MIMO, beamforming, and cooperative communications in various 5G implementations (Lin *et al.,*2019).Millimeter Wave: Operating within the frequency band of 30 GHz to 300 GHz, millimeter wave technology employs waves ranging from 1 to 10 mm. Originally utilized in radar applications, it is now integrated with 5G to enhance spectrum bandwidth and utilization. The pairing addresses congestion issues associated with standard technologies, offering a more extensive and less crowded spectrum (Rappaport *et al.,*2013)

Machine Learning Techniques: 5G networks employ supervised and unsupervised machine learning models to enhance overall network capacities, predict energy consumption, and optimize technologies like beamforming. Linear Regression Algorithms predict node scheduling, while Deep Neural Networks forecast beamforming vectors. Unsupervised learning models improve handover selection, reduce service interruptions, and decrease latency through fog node clustering (Dangi *et al*.,2021).Unmanned Aerial Vehicles (UAV): A groundbreaking proposal involves utilizing UAVs to enhance 5G network coverage. These aerial vehicles act as beacons, potentially solving interference problems and even replacing terrestrial cellular networks. Equipped with various sensors and devices, UAVs in the era of 5G and IoT offer applications in precision agriculture, industrial inspection, emergency response, disaster management, surveillance, and security. The combination of UAVs with 5G networks and IoT sensors opens up diverse possibilities across industries, promising improved efficiency, cost reduction, and enhanced safety (Huang *et al.,*2018)

2.2 The IoT Framework in 5G Networks

The IoT for 5G structure has four important layers that are responsible for data collection, processing, analysis, and sharing of resources between equipment and communication networks

(Khanh et al.,2022).These layers are categorized as follows: Thing layer: This layer includes physical systems such as actuators, objects, and sensors, and communicates with the network layer.

Network layer: The network layer is grouped into two subclasses which are low power wide area technologies (LPWANs) such as SigFox, LoRa, ZigBee, NB-IoT, and backhaul-based connections of 5G network (Khanh et al.,2022).Middleware layer: This is the heart of the network. The IoT framework is deployed on advanced technologies and solutions such as fog computing, edge computing, cloud computing, AI vision, and big data analytics.

Application layer: This is the application that is used to manage the operation of systems such as factories and smart buildings, agriculture, traffic systems, and IoT ecosystems. This layer integrates all solutions, technologies, and applications to interact with humans through the Internet connection. Samsung is providing IoT solutions that allow users to control home appliances.

A specific illustration of this architecture is presented in Figure 2. The sensor devices of IoT applications interact with the IoT gateway based on low-power communication networks such as SigFox, LoRa, or NB-IoT (Khanh et al.,2022). These IoT gateways collect information from IoT devices and then transmit it to the Cloud through the 5G backhaul communications. In the middleware layer, the collected data is processed and stored, combining autonomous decision-making as illustrated in Figure 2

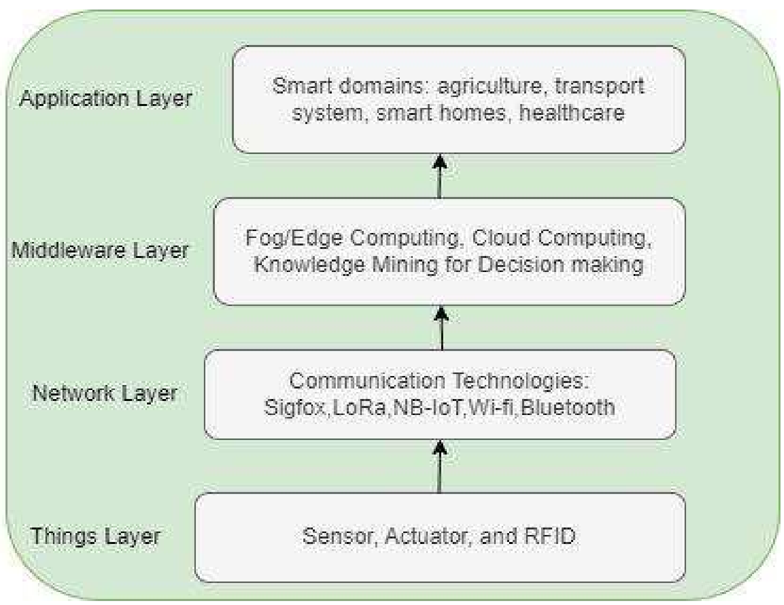

Figure 2. The IoT Framework in 5G Network

The work of Kar *et al.,*(2021), also examined the architecture of IoT in a 5G system that features several critical layers, where each addressing specific functions and challenges. At the foundational level, the Things Layer comprises smart IoT sensors deployed for various applications, which are integral to data collection and interaction with the environment. Above this, the Network Layer includes an IoT gateway that plays an important role in collecting and forwarding information between IoT devices and 5G base stations through wired and wireless networks. The 5G Network layer is for providing Ultra-Reliable Low-Latency Communications (URLLC) and Enhanced Mobile Broadband (eMBB) capabilities.This improves 5G NR (New Radio) technology and mmWave communication as presented in Figure 3

Figure 3: 5G IoT Architecture (Kar *et al.,*2021)

However, several challenges remain unresolved, including network mobility, coverage, reachability, scalability, latency, and reliability issues, which are critical areas of ongoing research and development (Kar *et al.,* 2021). To address these challenges, the authors integrate channel modules to establish effective communication. Despite these efforts, the work is limited to achieving optimal connectivity due to the path loss approach adopted for planning and installation of network equipment.

2.3 Comparison between 4G And 5G Networks

Kar et al. (2021) explore the transition from 4G to 5G network architectures, highlighting key differences and their implications for path loss management in 5G IoT systems. They emphasize significant advancements in latency reduction, with 5G aiming for as low as 1ms latency compared to the higher latency of 4G, achieved through advanced channel modules integration. Furthermore, they discuss the exponential increase in potential download speeds from 1Gbps in 4G to over 10 Gbps in 5G, facilitated by the integration of 5G NR technology and mmWave communication. The authors also delve into changes in base station deployment, from macro base stations in 4G to a dense network of small cells and macro cells in 5G, strategically placed to optimize coverage and connectivity, which is essential for minimizing path loss effects. Moreover, they highlight the evolution of OFDM encoding from 4G to 5G, enabling better handling of diverse applications and scenarios and contributing to improved network performance and reduced path loss. However, the authors did not use empirical path loss, or deterministic models for their assessment of system performance. This system may not be suitable in large city environments.

2.4 Application of IoT in 5G Network

Vehicle Tracking and Connectivity: Streamlined IoT connectivity enables effective vehicle tracking for logistics companies, including 3PLs and 4PLs, delivery vehicles (white goods, and food delivery aggregators), as well as cab companies and aggregators. Connected cars benefit from seamless, low-latency connectivity, fostering communication with other vehicles, network infrastructure, and the broader road infrastructure. This interconnected environment enhances overall road safety and traffic efficiency. Telematics plays a pivotal role in collecting, storing, and transmitting essential information for regulating moving objects, particularly vehicles. Leveraging mobile phone capabilities, IoT sensors in vehicles monitor parameters like speed, fuel consumption, and tire pressure. These data points enable the generation of alerts, contributing to improved safety. The integration of IoT devices introduces additional intuitive features, elevating the overall driving experience (Khanh et al.,2022).

Automation of Smart Grid: The 5G facilitates the management of the smart grid by enhanced effectiveness compared to traditional grids. Customers benefit from high-quality services facilitated by Advanced Metering Infrastructure (AMI) and telemetry through IoT devices. Smart grid technology seamlessly integrates into a comprehensive system, empowering grid control, monitoring, and analysis to ensure the safe and reliable delivery of electric power to all. This technology enables real-time monitoring and hybrid systems, significantly increasing the likelihood of detecting and anticipating faults promptly. The integration of intelligent electrical networks and digital communication technology creates an advanced smart grid, facilitating quick and efficient solutions to challenges within the power distribution system.

Remote Surveillance: The 5G network is equipped with IoT sensors that drive remote video surveillance, allowing observation of production lines and high-security zones with ultra-HD video quality. Video analytics is facilitated by the capabilities of 5G sensors, taking advantage of high-speed, low-latency transmissions. Consequently, IoT sensors send real-time alerts in instances where criminal, vandalism, or suspicious activities are identified.

Smart Traffick Staffing: 5G facilitates Intelligent Transportation by utilizing IoT sensors to collect real-time data from vehicles and road infrastructure. Immediate alerts are generated as traffic cabinets integrate these systems at city street intersections. Regular use of these systems can lead to cost savings, increased system reliability, and improved traffic safety and efficiency. These intelligent traffic control systems are equipped with IoT cameras, sensors, cellular routers, and automation, allowing for the comprehensive deployment of 5G network (Dangi et al.,2021)

Smart Manufacturing: In the manufacturing sector, the combination of 5G and IoT presents opportunities for process automation and predictive analytics through remote monitoring of production lines. This integration transforms workflows into instrumented digital processes, collecting data by seamlessly incorporating machines, operators, and sensors to achieve business objectives. Examples of the benefits of 5G's low latency, high speed, and high-definition video streaming capabilities in the realm of IoT include applications in repairs, Augmented Reality (AR), Collaborative Robotics, Precision mining, and smart manufacturing scenarios such as SCADA automation.

Healthcare System: low-latency Ultra HD video streaming and ambulances connected to hospitals through IoT sensors facilitate real-time patient tracking, enabling hospitals to prepare for immediate treatment. Integration of smart wearables and sensors in healthcare systems ensures continuous contact with doctors during surgeries, allowing patients to receive prompt medical attention that would be challenging to achieve manually. The combination of 5G network low-latency capabilities and IoT sensors further streamlines robotic surgeries.

Smart Homes/Cities: Utilizing the 5G network and IoT sensors, smart cities gather real-time data, analyze demand patterns, and swiftly implement cost-effective solutions. Homeowners can efficiently manage IoT sensors in appliances, lighting, thermostats, and other devices through 5G-connected smartphones and tablets. The ultra-low latency feature of 5G enhances the user experience in both Smart City and Smart Homes applications, providing a close-to-real-time interaction (Ge *et al.,*2019)

2.5 Different Path Loss Models Used for 5G Network Planning

IoT in 5G is an emerging technology in the communication and information technology area. It could be applied in a series of different domains from popular applications in life such as payment utilities, smart retail, and managing home appliances to expert apps such as self-driving vehicles, home monitoring, monitoring traffic status, collision warning between vehicles, and monitoring, and controlling green energy systems, smart cities management. IoT is deployed in agriculture for forest management, monitoring fire outbreaks, and tracking farm products. In the industrial area, actuators and robots with the support of AI technology can perform tasks day and night and replace humans with extremely high productivity and accuracy. It realizes the dream of smart and green factories. To improve on the optimal utilization of these IoT various path loss models have to be investigated to ascertain the suitable model for a particular network environment. This loss may be caused by factors such as reflection, diffraction, refraction, and scattering components which lead to poor signal transmission. The measurement of the spectrum aims to understand the channel behavior and to develop realistic and trustworthy path loss models.

These radio propagation models include deterministic models, empirical models, and machine learning approaches. Deterministic models are very complex because they require comprehensive information about the environment, dimension, and physical parameters that constitute an obstacle in the area. Empirical models obtained the parameter values by fitting measurement data to an appropriate function for a particular environment. However, the development of propagation models is important in designing a radio interface to optimize performance and deploying systems in the field for radio coverage determination. These models play a key role in engineering tools, predicting various values essential for the deployment of radio telecommunication systems, including site selection, frequency allocation, power definition, and interference description. The effectiveness of these models relies heavily on geographic datasets consisting of topography and land use types. Ultra-high frequency (UHF) radio wave propagation is intricately linked to the obstacles encountered in a given space, such as buildings, tree trunks, and mountainsides. Therefore, the modeling of geographical objects becomes indispensable in any UHF wave propagation model (Faruk *et al.,*2019)

These models serve as a mathematical prediction of wave propagation between the origin and destination service area. This prediction enables a system receiver to assess the adequacy of a planned radio system in serving the desired service area. The subsequent sections delve into the fundamental models under study, their classification, data requirements, and coverage considerations. The empirical and semi-model parameters are further discussed as:

The Okumura–Hata model: This model is used in a roughly even surface for distances limited to 30km, with the highest transmitter antenna heights of 200m and receiver antenna heights of 10m as depicted in Equation (1).

$$L_u = 69.55 + 26.16\log_{10}(f) - 13.82\log_{10}(h_b) - ah_m\log_{10}(d) \qquad (1)$$

where f is the frequency in MHz, hb the base station antenna height in meters above the averaged (averaged over 3–15 km) terrain height, ah_m the mobile antenna height correction factor, and d the distance between the transmitter and the receiver in kilometers (Al-Safwani and Sheikh, 2003). This model is limited to indoor coverage and does not consider terrain irregularities.

The COST 231 Hata model: It utilizes a wider frequency spectrum and it is suitable in urban, suburban, and rural areas because of its simplicity and the availability of correction factors. The model is characterized by a frequency range of 500 MHz to 2000 MHz, transmitter height of 30m to 100m, link distance of about 20 km, and mobile station (MS) height of 1 m to 10m as depicted in Equation (2) (Mishra *et al.,*2019)

$$L = 46.3 + 33.9logf - 13.82logh_B - a(h_R) + (44.9 - 6.55logh_B)logd + C \qquad (2)$$

$where, C$ for medium cities and suburban areas, metropolitan areas, L is median path loss in Decibels (dB), f is frequency of transmission in Megahertz (MHz), h_B is base station antenna effective height in Meters (m), d is the distance in Kilometers (km), h_R is mobile station antenna effective height in meters (m), $a(h_R)$ is the Mobile station Antenna height correction factor as described in the Hata model for urban Areas. This model does not capture the complexity of real-world scenarios accurately.

Walfisch–Ikegami Model: This model is used for determining the path loss in the urban area and operates in a frequency range of 800 to 2000 MHz and within a range of 0.02 to 5km as depicted in Equation (3) (Mollel,and Michael, 2014).

$$L_{los} = 42.6 + 26logR + 20logf \qquad (3)$$

Where R is the distance, and f is the frequency. The model is limited by the high cost of implementation

Stanford University Interim (SUI) Model: This propagation model is derived from the Hata model, operating in frequencies exceeding 1900 MHz, allowing correction parameters to extend its applicability up to the 3.5 GHz band. In the United States, it is used in Multipoint Microwave Distribution System (MMDS) within the frequency range of 2.5 GHz to 2.7 GHz. The SUI model utilizes the base station antenna height ranging from 10 m to 80 m, while the receiver antenna height spans from 2 m to 10 m. The cell radius is determined within the range of 0.1 km to 8 km. The SUI model categorizes terrain into three types: terrain A, terrain B, and terrain C, without specifying any particular environmental conditions as depicted in Equation (4) (Sotiroudis et al.,2013)

$$L = A + 10\gamma \log\left(\frac{d}{d_o}\right) + X_f + X_h + S \; for \; d > d_o \qquad (4)$$

where, X_f $is\ correction\ frequency$, f is the operating frequency in MHz, and $h + s$ is the receiver antenna height in meters and d is the distance in meters, X_h is the correction for receiving antenna height, S is the correction for shadowing in dB and γ is the path loss exponent. However, this model assumes a homogeneous environment, which may not accurately represent the diversity of real-world terrains and urban structures.

ECC-33 or Extended Hata-Okumura model: This model is proposed for mobile systems with omnidirectional receiver antennas sited less than 3 m above ground level and a frequency range of about 2 GHz. It is given by Equation (5) (Mollel,and Michael, 2014).

$$L = A_{fs} + A_{bm} - G_b - G_r \qquad (5)$$

Where, A_{fs} , A_{bm} , G_b and G_r are the free space attenuation, the basic median path loss, the Base station height gain factor, and the receiver height gain factor. ECC-33 may not functionally at extremely high or low frequencies.

Ericsson model: This model is derived from the Okumura-Hata model designed to accommodate adjustments in parameters based on the dynamic propagation environment and depicted in Equation(6) (Mollel,and Michael, 2014).

$$L = a_o + a_1 \log(d) + a_2 \log(h_b) + a_3 \log(h_r) \log(d) - 3.2\log(11.75h_r)^2 + g(f) \qquad (6)$$

where parameters $f$are the frequency in (MHz), h_b is the transmission antenna height in (m), h_r is the Receiver antenna height in (m). The default values of these parameters (a_o , a_1 , a_2 and a_3) for different terrains. The model is designed mainly for Ericsson's network equipment and technologies, which limits its usability.

Free Space Model: This model computes the amount of signal loss during propagation from transmitter to receiver. The free Space Model is determined by frequency and distance and is given by Equation (7) Mollel,and Michael,2014).

$$L = 32.45 + 20\log(f) + 20\log(d) \tag{7}$$

Where $f$are frequency and $d$is distance. This model is not suitable for indoor environments and does not consider shadowing and multipath effects for its prediction.

WINNER II Model: This model is a system-level model, which describes an arbitrary number of propagation environment realizations for single or multiple radio links for all the defined scenarios for specific antenna configurations, with one mathematical framework by different parameter sets as depicted in Equation (8).

$$PL = 20logd + B + C\log_{10}\left(\frac{f}{5}\right) + X \tag{8}$$

where d is the distance between the transmitter and the receiver in meters (m), f is the system frequency in (GHz), the fitting parameter A includes the path-loss exponent, parameter B is the intercept, parameter C describes the path loss frequency dependence, and X is an optional, environment-specific term. It is complex to implement.

ITU-R Model: The ITU-R model for indoor attenuation is a radio propagation model designed to estimate path loss within enclosed spaces, such as rooms or closed areas delimited by various wall configurations inside a building. Specifically designed for devices for indoor use, this model provides an approximation of the overall path loss that an indoor communication link might encounter as depicted in Equation (9).

$$PL(dB) = 20\log_{10} f + N\log_{10} d + P_f(n) - 28 \tag{9}$$

$PL\ (dB)$ is the total path loss, $f\ (MHz)$ is frequency of transmission, $d\ (m)$ is distance, N is distance power loss coefficient, n is Number of floors between the transmitter and receiver and $Pf(n)$ is floor loss penetration factor. However, this model always assumes static antenna heights for both transmitter and receiver which may not reflect dynamic real-world scenarios. This results in discrepancies in predicted and actual signal transmission. However, Artificial Intelligence (AI) is a robust tool used in addressing challenges where conventional solutions involve extensive manual tuning or intricate rule formulations. It effectively handles complex issues that lack feasible solutions through traditional methods (Asuquo *et al.,*2020)

AI is particularly valuable for adapting to dynamic environments, by learning patterns and extracting the relationship between the variables that may elude human observation. AI systems can autonomously learn from historical data, identify anomalies, make predictions about future events, and more. Utilizing AI learning capabilities, coupled with extensive datasets in areas like signal propagation or wireless configurations, proves instrumental in tackling these complex problems. One of the most significant challenges in communication systems is the potential loss of information during transmission from the transmitter to the receiver. The ascent of 5G network technology is increasingly recognized as a pivotal solution for Broadband Wireless Access (BWA). Within frequency ranges below 11 GHz, 5G, alongside WiMAX, operates seamlessly in both line-of-sight

(LOS) and non-line-of-sight (NLOS) scenarios. The global deployment of 5G and associated networks, including WiMAX, is advancing at a rapid pace. Accurately estimating path loss becomes important in the initial stages of deploying wireless networks and designing cells, especially with the integration of the Internet of Things (IoT) in the 5G landscape. Various path loss models, such as the Okumura Model and Hata Model, are available for predicting propagation loss. However, they remain confined by specific parameters in the context of evolving technologies in 5G and IoT.

Optimizing service quality in wireless networks with an improved Erlang-B dynamic channel allocation (MEB-DCA) scheme was presented in (Asuquo *et al.,*2020). The works did not consider parameters that influence signal loss in the path. The study only represents the statistics of the path loss at a given distance, but it cannot estimate the optimal received power at a specific location. Learning-based approach for self-optimization in SON deployments and key performance indicators (KPIs) deployed for the selection of optimal network configuration was proposed by (Bojović et al.,206). This approach facilitates the dynamic frequency and bandwidth assignments (DFBA) in long-term evolution (LTE) residential small cell network deployments. The RMSE used to evaluate system performance and results show that the learning-based DFBA yields on average a performance improvement of 33 % over approaches that are based on analytical models, reaching 95 % of the optimal network performance while leveraging just a small number of network measurements. However, it does not look into the specific optimization metrics used for assessing network efficiency and resource utilization. An unsupervised-learning-based method for eNB to select relay nodes to help broadcast was investigated in (Song *et al.,*2017). The eNB investigates the distribution of vehicles and classifies them to determine a robust broadcast approach. The result emphasizes that a larger communication range correlates with improved D2D communication capabilities among vehicles, with a significant portion of cars achieving efficient data reception in a single time slot, particularly at extended communication ranges. However, eNB's reliance on knowing the number of clusters before initiating the selection method introduces a time-consuming step to find the optimal cluster value. Big data analytics in the form of call detail records (CDR) from mobile networks to achieve two main objectives were employed (Parwez *et al.,*2017). The unsupervised clustering techniques (k-means and hierarchical clustering) were used for anomaly detection in mobile wireless networks.

The detected anomalies are compared with ground truth information to determine their accuracy, indicating that abrupt increases in traffic demand are identified as anomalies. This information identifies regions of interest for specific actions, such as resource allocation or fault avoidance. The neural network-based prediction model was used to train and obtain both anomalous and anomaly-free data. The transformation of anomalous data to anomaly-free data greatly reduces the error in prediction during model training compared to training with anomalous data. MSE for training, validation, and test data is significantly higher when the prediction model is applied to data with anomalies and reduces after removing anomalies among training, validation, and test data. However, users' contextual information, such as mobility patterns, traffic patterns, content preferences, and social networks was not considered. Base station prediction and proactive mobility management in virtual cells using recurrent neural networks (RNN) (Wickramasuriya *et al.,*2017). A total of 70,000 sequences were selected for training and 30,000 sequences were used for testing the RNN. The result shows that 100 training epochs were done, the testing error abruptly converged and a maximum accuracy of 98.3% was obtained in this 8-class sequence classification problem. However, different levels of quality of service (QoS) constraints per user were not considered by the author. Machine Learning Aided Cognitive RAT (Radio Access Technology) Selection for 5G Heterogeneous Networks was examined in (Perez et al.,2017)

The primary goal was to determine cognitive capabilities at the device level, allowing devices to learn optimal decision policies based on their own experiences and achieve reasonably high-performing decision-making processes. The results show that Q-learning, a machine learning algorithm, outperformed alternative decision mechanisms. On average, Q-learning yielded 40% higher rewards compared to the max-SINR (Signal-to-Interference-plus-Noise Ratio) algorithm and approximately 15% higher rewards compared to a random decision-making mechanism. This improved performance was directly attributed to the Q-learning algorithm's ability to enhance network load balancing. Machine-learning methods based on a Hidden Markov Model (HMM) to address the challenges associated with Massive Machine-Type Communication (mMTC) in emerging 5G networks were presented in (Balapuwaduge, & Li, 2019). The HMM is employed to enable optimal cell association for mMTC devices, allowing them to make informed decisions regarding the most appropriate eNodeB for data transmission. Poisson and Beta arrival distributions are applied to evaluate the performance under different MTC traffic conditions with Beta (3, 4), to represent bursty traffic conditions. This shows that proposed cell selection approaches outperform the random selection when MTC traffic is bursty. However, there is the problem of capturing complex relationships among the variables. Nine different optimization algorithms, namely Gauss-Newton (GN), gradient descent (GD), Genetic Algorithm (GA), Levenberg-Marguardt (LM), Quasi-Newton (QN), Trust-Region-Dog-Leg (TR), pattern search (PAS), Simulated Annealing (SA), and particle swarm (PS) were employed in (Isabona et al.,2023). The optimization algorithms were benchmarked against measured data obtained from various radio signal propagation terrains around four eNodeB cells. The benchmarking criteria included the Accuracy Profile Benchmark (APB), Function Evaluation Benchmark (FEB), and Execution Speed Benchmark (ESB). The results show that the Quasi-Newton (QN) method exhibited the least optimization error with MAPE values of 3.6319 in location 1, 2.6909 in location 2, 2.676 in location 3, and 3.6560 in location 4. This suggests that QN provided the best prediction accuracies among the evaluated algorithms. A comprehensive approach including data collection, statistical analysis, and optimization techniques to assess the quality of Mobile Broadband (MBB) services in three different locations in Lagos, Nigeria in (Imoize et al.,2023). Minimal optimization techniques using Particle Swarm Optimization (PSO) were applied to address identified issues. Key Performance Indicators (KPIs) for MBB services were measured, including Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), Received Signal Strength Indicator (RSSI), and Signal-to-Noise Ratio (SINR). The results show that PSO optimization significantly reduced the RMSE for RSSI by −59.30 dBm, the PSO optimization achieved a significant reduction in RMSE for RSRP, amounting to −58.40 dBm and the improvement in RMSE for Reference Signal Received Quality (RSRQ) was noted as −5.24 dB. However, the study is limited by the high cost of implementation

2.6 Network Radio (NR) for IoT Connectivity in 5G

NR for both licensed and unlicensed incorporates several essential features to support diverse network deployment scenarios, terminal requirements, and applications over IoT connectivity is discussed and presented in (Kim *et al.,*2019)

2.6.1 Bandwidth Part (BWP)

BWP is a segment of the carrier bandwidth configured for a UE. Unlike LTE/LTE-Advanced, where a UE monitors the entire 20 MHz bandwidth, NR's larger bandwidth can lead to excessive power consumption if the same approach is used. For instance, voice calls, which need less than 100kbps, can be efficiently handled with less than 5MHz. Using the entire carrier bandwidth for such low-rate services would unnecessarily increase power consumption due to high sampling rates. BWP allows the UE to monitor a smaller, application-specific portion of the bandwidth, reducing power usage. A UE can be configured with up to four BWPs per carrier, each with a configurable size and location. Only one BWP is active at a time, but the UE can switch between them to match the required data rate and select the smallest BWP when idle to conserve power However, the ineffective path loss approach will hinder optimal utilization of the service.

2.6.2 Codeblock Group (CBG)-Based Retransmission
Unique to NR, CBG-based retransmission divides a transport block (TB) into up to eight CBGs. Each CBG can receive individual hybrid automatic repeat request acknowledgments (HARQ-ACK) from the receiving side, indicating which CBGs were received correctly. This feature is beneficial for delay-tolerant data transmissions that might be partially corrupted by urgent data packets. CBG-based retransmission uses fewer time-frequency resources, improving performance by making more room for other data.

2.6.3 Multi-Beam Operation
While multi-antenna technology in LTE-Advanced focuses on maximizing spectral efficiency, NR uses it to ensure adequate coverage, particularly in frequency range 2 (FR2), where signal propagation loss is significant. For example, 28 GHz signals attenuate 100 times more than 2 GHz signals. NR employs multi-beam operation, creating multiple highly directional beams with numerous antenna elements to mitigate this loss. Data transmission utilizes the beam with the best signal quality at any given moment. NR specifications support measurement, selection, and assignment to facilitate effective multi-beam operation.

2.6.4 Comparison of Network Radio Unlicensed (NR-U)and NR-Licenced (NR- L)Spectrum in 5G Networks

The primary challenge for NR-U is meeting the regulatory requirement that a transmitter must sense the channel before talking to ensure fair coexistence with other devices operating in the same unlicensed spectrum. Unlike NR in licensed spectrum, critical signals and channels for communication, such as those for synchronization, control, and random access, cannot be transmitted on unlicensed spectrum unless it is first determined that the channel is idle. Consequently, NR-U will emphasize specification support to create additional transmission and reception opportunities for these essential signals and channels (Kim *et al.,*2019). Another significant challenge is addressing the problem of ineffective path loss. In unlicensed spectrum, signal propagation can be unpredictable and inconsistent due to varying environmental factors, leading to suboptimal performance. This issue necessitates the development of robust strategies to manage path loss effectively and ensure reliable communication. NR-U must incorporate advanced techniques to mitigate these challenges and maintain high-quality service.

2.7 Issues for IoT in 5G Networks Implementation

The 5G network represents a significant advancement in mobile communication technologies, several issues spanning technological complexities, security and privacy implications, and social considerations have emerged.

2.7.1 Technical Complications
The primary technical challenge revolves around interference, with 5G being notably sensitive to disruptions, even from mild rain in urbanized areas. Despite efforts to mitigate these challenges through technologies like massive MIMO and millimeter waves, scalability remains a concern. Tests conducted in various countries using small cells highlight the necessity for more extensive architectures to ensure comprehensive coverage and an optimal user experience (Borralho *et al.,*2021)

2.7.2 Coverage Disparities

The need for extensive and costly infrastructures poses a dilemma, as providers may prioritize urban areas, potentially neglecting rural regions. This creates a divide in coverage and user experience, raising ethical concerns regarding unequal access to advanced communication technologies (Pons *et al .,*2023)

2.7.3 Ethical and Social Implications

The promise of improved connectivity for individuals in impoverished conditions, a key advantage of 5G, is hindered by the current high cost of 5G architectures and their limited reach in rural areas. While advancements are anticipated in the coming years, the present disparity poses ethical questions about the equitable distribution of technological benefits (Pons *et al .,*2023).The advent of the Internet of Vehicles (IoV) enabled by 5G introduces additional ethical and social challenges. The proliferation of autonomous driving cars, facilitated by 5G, brings forth moral dilemmas in instances where accidents occur due to autonomous vehicle actions. Moreover, connecting vehicles to the internet raises security concerns, such as the potential for remote vehicle hijacking by hackers (Pons *et al .,*2023)

However, the key problems in 5G implementation include technical intricacies related to interference, the necessity for extensive and expensive infrastructures favoring urban areas, ethical concerns regarding unequal connectivity opportunities, and security implications linked to the connectivity of vehicles to the internet. The resolution of these issues is critical for the widespread and equitable adoption of 5G technologies in diverse settings. However, utilizing empirical models in network planning can cause suboptimal connectivity when these models are applied to more complex and dynamic environments likely very densely populated areas (Robinson *et al.,*2010). There is a need to examine critically various challenges that can hinder optimal connectivity of IoT devices in future work as illustrated in Table 1

Table 1: Challenges for 5G Network and IoT Services.

5G Network	IoT Services	Issues
Security threats, including Distributed Denial of Service (DDoS) attacks, identity theft, and man-in-the-middle attacks, pose vulnerabilities to 5G networks.	IoT devices face security risks due to weak encryption, passwords, and outdated firmware.	Security
The lower latency in 5G networks can pose challenges for certain IoT applications that demand immediate responses.	Latency in IoT services may arise from network congestion, server distance, and the volume of connected devices.	Latency
Interference from other wireless devices can disrupt data transmission in 5G networks.	Environmental factors, like obstacles and interference from other wireless devices, harm IoT services.	Interference
The high cost of 5G infrastructure and services may pose a significant barrier for numerous IoT applications, especially those requiring large-scale deployment.	Deploying and maintaining IoT services can incur high costs, especially when necessitating high bandwidth or specialized hardware.	Cost
Planning for scalability is essential to accommodate the growing number of devices and users in both 5G and IoT environments	A well-designed network should be capable of scaling up to meet increasing demand without compromising performance.	Planning

Compatibility issues with 5G networks may restrict the utility of certain IoT devices in specific applications.	Compatibility issues, especially with reliance on proprietary hardware or software, can constrain the functionality of IoT services.	Compatibility

3. CONCLUSIONS

The evolution from 1G to 5G wireless communication systems has been driven by user demands and technological advancements. The transition from 4G to 5G marks a significant leap, primarily characterized by the extensive utilization of the Internet of Things (IoT). While 4G effectively addressed several key challenges, it laid the groundwork for the transformative capabilities of 5G, which is expected to connect billions of devices by 2030, as predicted by Cisco. This interconnected IoT ecosystem, facilitated by device-to-device (D2D) communications, spans numerous sectors. However, despite its promises, 5G IoT networks face challenges such as poor connectivity, quality of service (QoS) issues, energy utilization concerns, and privacy and security threats. This comprehensive survey delves into the critical role of path loss models in optimizing IoT connectivity within the 5G landscape, highlighting the contrast between 4G and 5G in this context. 4G networks primarily focused on improving data speeds and connectivity but were limited in supporting the massive device density and low-latency requirements essential for IoT. In contrast, 5G networks are designed to handle these demands more effectively, offering enhanced connectivity, reduced latency, higher data speeds, and improved network performance. To minimize overall energy consumption, IoT nodes in 5G leverage advanced technology scaling and low-power design methodologies. Future IoT devices, becoming increasingly context-aware and adaptable, will demand varied power supplies, necessitating an adaptable energy management system. High-power RF transmission for long-distance communication in 5G requires higher supply voltages, while short-range communication demands intermediate voltages. Additionally, sharing a power delivery network (PDN) among modules introduces a variable load to the power management unit (PMU). Integrating machine learning and evolutionary intelligence into path loss approaches underscores the importance of efficient energy management. Path loss, occurring as electromagnetic signals propagate through the environment, directly impacts the power requirements for RF transmission. By optimizing power management strategies in response to path loss variations, IoT devices can enhance communication reliability and extend battery life, ultimately improving overall system performance. This work provides comprehensive insights into the technological advancements driving the enhancement of path loss management in 5G IoT systems, aligning with the objectives of modern 5G networks. By effectively addressing the key differences between 4G and 5G network architectures and integrating advanced technologies to optimize network components, the concept will enhance path loss management in 5G IoT systems. Our contributions include delineating the characteristics of 5G networks, elucidating the architecture of IoT within the 5G framework, exploring various path loss models for network planning, and identifying research gaps for efficient IoT connectivity. By focusing on path loss modeling, this systematic review contributes to the goal of enhancing IoT connections in 5G networks.

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5. REFERENCES

[1] Agiwal, M., Kwon, H., Park, H., and Jin, H. (2021). A survey on 4G-5G dual connectivity: road to 5G implementation, IEEE Access, vol. 9, pp. 16193–16210

[2] Ali, G. M. N., Sadat, M. N., Miah, M. S., Sharief, S. A., & Wang, Y. (2023). A Comprehensive Study and Analysis of 3GPP's 5G New Radio for V2X Communication.

[3] Alnatoor, M., Omari, M., & Kaddi, M. (2022). Path loss models for cellular mobile networks using artificial intelligence technologies in different environments. *Applied Sciences*, *12*(24), 12757.

[4] Al-Safwani, M., & Sheikh, A. U. (2003). Signal strength measurements at VHF in the eastern region of Saudi Arabia. *Arabian journal for science and Engineering*, *28*(2 C), 3-18.

[5] An, J., Le Gall, F., Kim, J., Yun, J., Hwang, J., Bauer, M., ... & Song, J. (2019). Toward global IoT-enabled smart cities interworking using adaptive semantic adapter. *IEEE Internet of Things Journal*, *6*(3), 5753-5765.

[6] Asuquo, D., Ekpenyong, M., Udoh, S., Robinson, S., & Attai, K. (2020). Optimized channel allocation in emerging mobile cellular networks. *Soft Computing*, *24*, 16361-16382.

[7] Balapuwaduge, I. A., & Li, F. Y. (2019, May). Hidden Markov model based machine learning for mMTC device cell association in 5G networks. In *ICC 2019-2019 IEEE International Conference on Communications (ICC)* (pp. 1-6). IEEE.

[8] Bojović, B., Meshkova, E., Baldo, N., Riihijärvi, J., & Petrova, M. (2016). Machine learning-based dynamic frequency and bandwidth allocation in self-organized LTE dense small cell deployments. *EURASIP Journal on Wireless Communications and Networking*, *2016*(1), 1-16.

[9] Borralho, R., Mohamed, A., Quddus, A. U., Vieira, P., & Tafazolli, R. (2021). A survey on coverage enhancement in cellular networks: Challenges and solutions for future deployments. *IEEE Communications Surveys & Tutorials*, *23*(2), 1302-1341.

[10] Chettri, L., and Bera, R. (2019). A comprehensive survey on Internet of Things (IoT) toward 5G wireless systems. *IEEE Internet of Things Journal*, *7*(1), 16-32.

[11] Cirillo, F., Gómez, D., Diez, L., Maestro, I. E., Gilbert, T. B. J., & Akhavan, R. (2020). Smart city IoT services creation through large-scale collaboration. *IEEE Internet of Things Journal*, *7*(6), 5267-5275.

[12] Dahlman, E., Parkvall, S., & Skold, J. (2016). *4G, LTE-advanced Pro and the Road to 5G*. Academic Press.

[13] Dangi, R., Lalwani, P., Choudhary, G., You, I., & Pau, G. (2021). Study and investigation on 5G technology: A systematic review. *Sensors*, *22*(1), 26.

[14] del Peral-Rosado, J. A., Raulefs, RLópez-Salcedo,. J. A., and Seco-Granados, G. (2017). Survey of cellular mobile radio localization methods from 1G to 5G. *IEEE Communications Surveys & Tutorials*, *20*(2), pp.1124-1148

[15] Faruk, N., Popoola, S. I., Surajudeen-Bakinde, N. T., Oloyede, A. A., Abdulkarim, A., Olawoyin, L. A., ... & Atayero, A. A. (2019). Path loss predictions in the VHF and UHF bands within urban environments: experimental investigation of empirical, heuristics and geospatial models. *IEEE access*, *7*, 77293-77307.

[16] Ge, X., Zhou, R., & Li, Q. (2019). 5G NFV-based tactile Internet for mission-critical IoT services. *IEEE Internet of Things Journal*, *7*(7), 6150-6163.

[17] Huang, H., & Savkin, A. V. (2018). A method for optimized deployment of unmanned aerial vehicles for maximum coverage and minimum interference in cellular networks. *IEEE Transactions on Industrial Informatics*, *15*(5), 2638-2647.

[18] Imoize, A. L., Udeji, F., Isabona, J., & Lee, C. C. (2023). Optimizing the Quality of Service of Mobile Broadband Networks for a Dense Urban Environment. *Future Internet*, *15*(5), 181.

[19] Isabona, J., Imoize, A. L., Akinwumi, O. A., Omasheye, O. R., Oghu, E., Lee, C. C., & Li, C. T. (2023). Optimal Radio Propagation Modeling and Parametric Tuning Using Optimization Algorithms. *Information*, *14*(11), 621.

[20] Kar, S., Mishra, P., & Wang, K. C. (2021, October). 5G-IoT architecture for next generation smart systems. In *2021 IEEE 4th 5G World Forum (5GWF)* (pp. 241-246). IEEE.

[21] Khanh, Q. V., Hoai, N. V., Manh, L. D., Le, A. N., & Jeon, G. (2022). Wireless communication technologies for IoT in 5G: Vision, applications, and challenges. *Wireless Communications and Mobile Computing*, *2022*, 1-12.

[22] Kim, Y., Kim, Y., Oh, J., Ji, H., Yeo, J., Choi, S., ... & Lee, J. (2019). New radio (NR) and its evolution toward 5G-advanced. *IEEE Wireless Communications*, *26*(3), 2-7.

[23] Lin, Z., Lin, M., Wang, J. B., De Cola, T., & Wang, J. (2019). Joint beamforming and power allocation for satellite-terrestrial integrated networks with non-orthogonal multiple access. *IEEE Journal of Selected Topics in Signal Processing*, *13*(3), 657-670.

[24] Mishra, R., Kuchhal, P., & Kumar, A. (2018). Antenna Path Loss Propagation in the Dehradun Region at 1800 MHz in L-Band. In *Proceedings of the International Conference on Microelectronics, Computing & Communication Systems: MCCS 2015* (pp. 171-179). Springer Singapore.

[25] Mollel, M., & Michael, K. (2014). Comparison of empirical propagation path loss models for mobile communication.

[26] Neto, A. J., Zhao, Z., Rodrigues, J. J., Camboim, H. B., & Braun, T. (2018). Fog-based crime-assistance in smart iot transportation system. *IEEE access*, *6*, 11101-11111.

[27] Parwez, M. S., Rawat, D. B., & Garuba, M. (2017). Big data analytics for user-activity analysis and user-anomaly detection in mobile wireless network. *IEEE Transactions on Industrial Informatics*, *13*(4), 2058-2065.

[28] Perez, J. S., Jayaweera, S. K., & Lane, S. (2017, June). Machine learning aided cognitive RAT selection for 5G heterogeneous networks. In *2017 IEEE International Black Sea Conference on Communications and Networking (BlackSeaCom)* (pp. 1-5). IEEE.

[29] Pons, M., Valenzuela, E., Rodríguez, B., Nolazco-Flores, J. A., & Del-Valle-Soto, C. (2023). Utilization of 5G Technologies in IoT Applications: Current Limitations by Interference and Network Optimization Difficulties—A Review. *Sensors*, *23*(8), 3876.

[30] Rappaport, T. S., Sun, S., Mayzus, R., Zhao, H., Azar, Y., Wang, K., ... & Gutierrez, F. (2013). Millimeter wave mobile communications for 5G cellular: It will work!. *IEEE access*, *1*, 335-349.

[31] Robinson, S., Isabona, J., & Ekpenyong, M. (2010). Macrocellular propagation prediction for wireless communications in urban environments. *Journal of Computer Science and Technology*, *10*(03), 130-136.

[32] Samad, M. A., Choi, D. Y., & Choi, K. (2023). Path loss measurement and modeling of 5G network in emergency indoor stairwell at 3.7 and 28 GHz. *PloS one*, *18*(3), e0282781.

[33] Sinche, S., Raposo, D., Armando, N., Rodrigues, A., Boavida, F., Pereira, V., and Silva, J. S. (2019). A survey of IoT management protocols and frameworks. *IEEE Communications Surveys & Tutorials*, *22*(2), 1168-1190.

[34] Song, W., Zeng, F., Hu, J., Wang, Z., & Mao, X. (2017, June). An unsupervised-learning-based method for multi-hop wireless broadcast relay selection in urban vehicular networks. In *2017 IEEE 85th vehicular technology conference (VTC Spring)* (pp. 1-5). IEEE.

[35] Sotiroudis, S. P., Goudos, S. K., Gotsis, K. A., Siakavara, K., & Sahalos, J. N. (2013). Application of a composite differential evolution algorithm in optimal neural network design for propagation path-loss prediction in mobile communication systems. *IEEE Antennas and Wireless Propagation Letters*, *12*, 364-367.

[36] Stoyanova, M., Nikoloudakis, Y., Panagiotakis, S., Pallis, E., and Markakis, E. K. (2020). A survey on the internet of things (IoT) forensics: challenges, approaches, and open issues. *IEEE Communications Surveys & Tutorials*, *22*(2), 1191-1221.

[37] Wickramasuriya, D. S., Perumalla, C. A., Davaslioglu, K., & Gitlin, R. D. (2017, April). Base station prediction and proactive mobility management in virtual cells using recurrent neural networks. In *2017 IEEE 18th Wireless and Microwave Technology Conference (WAMICON)* (pp. 1-6). IEEE.

[38] Zhu, F., Lv, Y., Chen, Y., Wang, X., Xiong, G., & Wang, F. Y. (2019). Parallel transportation systems: Toward IoT-enabled smart urban traffic control and management. *IEEE Transactions on Intelligent Transportation Systems*, *21*(10), 4063-4071.

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