Topic: PATH LOSS PREDICTION FOR FIFTH GENERATION WIRELESS COMMUNICATION DEVICES: CHANNEL MODELLING FOR MOBILE PHONE NETWORK USING DEEP LEARNING TECHNIQUES

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1.2 Statement of the Problem

Path loss in wireless communication networks, characterised by the diminishing signal strength as radio waves traverse the environment, poses a significant challenge influencing both humans and technology. The detrimental impact of high path loss amplifies the problem, resulting in weakened signals known as poor Quality of Service (QoS) (Sharma & Singh, 2010; Joseph et al., 2023). This decline in signal quality adversely affects call quality, data transfer speeds, and network performance, impeding user experiences in activities such as online work, education, and communication.

Moreover, the consequences of high path loss contribute to a digital divide, restricting access to crucial services like emergency communication and online resources. Limited network coverage in areas with substantial path loss leaves users with irregular or no network access. To address this, Mobile Network Operators (MNOs) resort to increasing transmission power, exacerbating the problem by causing increased power consumption for both end users and network operators, leading to faster battery drain and higher energy consumption. Ilenikhena et al., 2019, found that high path loss leads to up to 30% more battery drain for mobile devices similarly (Israr et al., 2021).

Furthermore, lower signal strength resulting from high path loss contributes to increased network congestion and inefficiency (Idogho & George 2022). This congestion arises as users concentrate on available cells, impacting network capacity and efficiency (Banday et al., 2019). Inaccurate path loss prediction compounds the issue, leading to interference and the wastage of valuable spectrum and energy (Nwalozie et al., 2014). The crux of the matter is that precise path loss prediction is indispensable for effective network planning, deployment, and optimization, ensuring efficient coverage, resource allocation, and network.

The advent of Fifth Generation (5G) wireless networks introduces unprecedented challenges due to amplified path loss, especially in higher frequencies like millimeter waves (Nguyen & Cheema, 2021). Traditional methods for predicting path loss are insufficient in these intricate 5G scenarios. Consequently, the exploration of advanced techniques, such as deep learning, becomes imperative for more precise modelling. The aim of this research is to predict path loss in complex environments, particularly focusing on the distinctive challenges posed by the 5G landscape. This research aligns with the pressing need to enhance the accuracy of path loss prediction methods to ensure the optimal performance of 5G networks and unlock their transformative potential.

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Frequency

In the context of wireless communication, frequency refers to the number of cycles of a periodic waveform that occur in one second. It is often measured in hertz (Hz), where one hertz is equivalent to one cycle per second. In the electromagnetic spectrum, frequencies are associated with different types of wireless communication technologies.

Low Frequencies (e.g., AM Radio, FM Radio, TV): These frequencies range from kilohertz (kHz) to megahertz (MHz). They are suitable for long-range communication but may have limitations in terms of data transfer rates.

Medium Frequencies (e.g., Wi-Fi, Bluetooth): In the gigahertz (GHz) range, these frequencies provide a balance between range and data transfer rates. They are commonly used for local wireless networks.

High Frequencies (e.g., 4G LTE, 5G): Frequencies in the tens of gigahertz (GHz) range and above are considered high frequencies. They enable high data transfer rates but have shorter range and may be more susceptible to obstacles.

Millimeter Wave (mmWave): Millimeter waves are a specific range of high-frequency electromagnetic waves, typically in the frequency range from 30 gigahertz (GHz) to 300 gigahertz (GHz). This range corresponds to wavelengths in the millimeter range. Millimeter waves are part of the microwave portion of the electromagnetic spectrum.

Table 1 offers a comprehensive overview, comparing different frequency ranges in terms of characteristics, bandwidth, data rates, applications, and how each connects to your research on path loss prediction for 5G wireless communication devices.

Table 1:comprehensive overview of different frequency ranges

Frequency Range	Characteristics	Bandwidth	Data Rates	Applications	Connection to Research
Low Frequencies	Low kHz to MHz, long wavelengths, longer propagation	Low	Moderate	AM Radio, FM Radio, TV	Understanding low frequencies provides a basis for contrasting with higher frequencies in 5G.

Medium Frequencies	GHz range, balanced range and data rates	Moderate to High	Moderate to High	Wi-Fi, Bluetooth	Contextualising medium frequencies aids in appreciating advancements in 5G.
High Frequencies	Tens of GHz, higher data rates, shorter range	High	High	4G LTE, 5G	The focus of the research, addressing challenges posed by the shorter range of higher frequencies.
Millimeter Wave (mmWave)	30 GHz to 300 GHz, very short wavelengths, short range	Very High	Very High	5G Networks, Wireless Communication	Investigating path loss prediction in mmWave frequencies, addressing their shorter range and challenges.

~~**(PP)The Interplay of Frequency, Path Loss, and Reliable Communication in Diverse Environments**~~

2.1 Complex Environment

The complex environment of concern in wireless communication involves a myriad of contributing factors. High frequencies, including millimeter waves, dynamic user mobility, obstacles and reflections, weather conditions, network density, and device diversity collectively shape the intricacies of signal propagation in 5G networks.

In wireless communication, the utilization of multiple frequency bands is a pivotal element, each presenting distinct propagation obstacles and characteristics. The allure of higher frequencies, notably within the millimeter-wave (mmWave) spectrum supported by 5G technology, lies in their unparalleled data rates and capacity potentials. However, this advantage comes with a trade-off, as higher frequencies are more susceptible to path loss, primarily due to elevated mmWave absorption rates by physical barriers and atmospheric gases (Rappaport et al., 2014; Ghosh et al., 2020). Overcoming this challenge necessitates a comprehensive approach encompassing network densification, beamforming, adaptive modulation and coding, and channel modeling.

The quest for dependable communication in diverse settings mandates accurate path loss prediction achieved through thorough environmental characterization, accounting for variables like vegetation, topography, and building density (Idogho & George, 2022). Optimizing data transmission for dynamic channel circumstances involves constantly adjusting coding rates and modulation schemes to counteract fading and maximize signal strength (Ahn et al., 2020). To concentrate radio waves, mitigate the impact of path loss, and enhance signal directivity in specific locations, directional antennas and sophisticated beamforming algorithms are employed (Israr et al., 2021). The strategic deployment of microcells and picocells, smaller cell sites, helps minimize route loss effects, providing tighter coverage and reducing dependence on long-distance transmissions (Zhou et al., 2022).

By intentionally manipulating propagation characteristics through these techniques, the research aims to alleviate the constraints imposed by path loss, unlocking the full potential of high-frequency bands for reliable and comprehensive communication in diverse settings. This transformative approach heralds a new era in wireless networking, paving the way for immersive augmented reality experiences and ultra-reliable low-latency communication for driverless cars.

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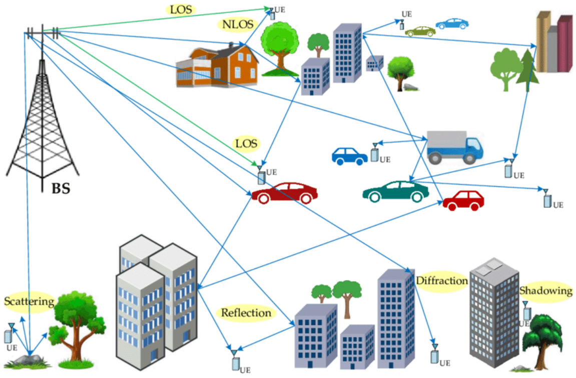
CHAPTER TWO

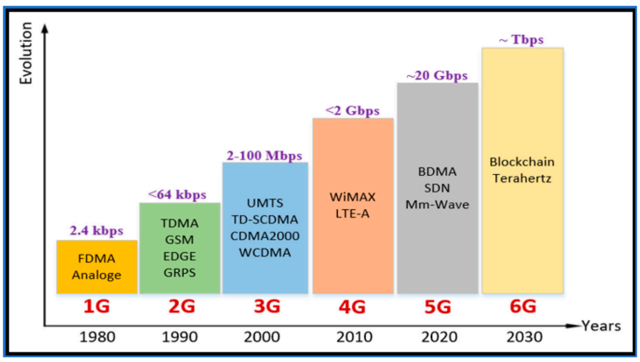
LITRATURE REVIEW

2.0 Introduction

In the context of wireless communication, path loss (Joseph & Roberts 2023), influenced by distance, obstacles, and environmental conditions have far-reaching consequences affecting both humans and technology of our everyday life. Despite advancement of research study and technological advancement identified gaps need to be field in the study of wireless communication channel modelling path loss. This chapter aim to achieve to fill the gaps in literature. The chapter provides recent, relevant and related literature including theoretical and conceptual foundation of the research.

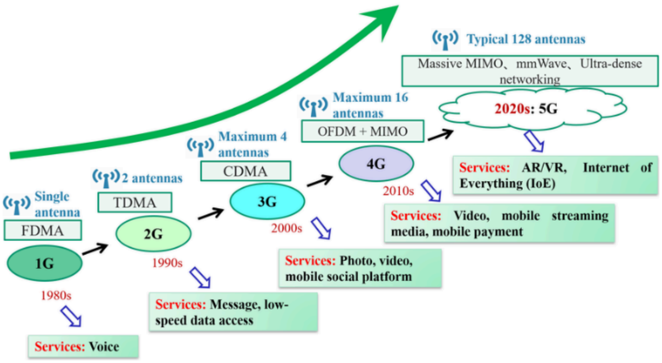


In navigating the challenges posed by path loss in the context of 5G, the literature review aims to delve into existing research, methodologies, and technological advancements. This exploration will lay the groundwork for the subsequent phases of the research, focusing on the path loss prediction for 5G wireless communication devices through advanced techniques, specifically deep learning methodologies.



2.1 Complex Environment

Signal propagation in 5G networks faces a complex interplay of factors. High frequencies, including millimeter waves, dynamic user mobility, obstacles and reflections, weather conditions, network density, and device diversity collectively shape the intricacies of signal propagation in 5G networks.



In the realm of 5G wireless communication, the utilization of millimeter-wave frequencies presents an enticing potential for high bandwidth, albeit encountering heightened signal attenuation due to atmospheric absorption and obstacles (Banday et al., 2019)[8]. Path loss models (Alnatoo et al., 2022)[10] have been proposed, exploring mitigation strategies through adaptive modulation, directional antennas, and network densification (MacCartney et al., 2013)[9].

Signal propagation dynamics fluctuate across urban, suburban, and rural landscapes due to diverse obstacles such as buildings and vegetation, with terrain contributing to diffraction and shadowing (Idogho & George, 2022)[5]. Context-specific path loss models like the COST 231 model for urban areas and the Hata-Okumura model for rural settings are employed (Ukatu et al., 2022)[11]. Research pivots toward adaptive mechanisms adjusting transmission parameters based on real-time environmental conditions (Alnatoo et al., 2022)[10].

User mobility introduces challenges in maintaining seamless connectivity during handovers between base stations (Tuyisenge et al., 2020)[7]. Exploration of optimization techniques and predictive methods based on movement patterns addresses this issue (Idogho & George, 2022)[5]. Efficient resource allocation for dynamic user demands and seamless handovers becomes pivotal for optimal network performance in 5G (MacCartney et al., 2013)[9].

Context-aware resource allocation schemes leveraging user profiles and mobility patterns are investigated (Tuyisenge et al., 2020)[7].

Environmental factors govern how radio waves travel, impacting signal strength. Researchers employ ray tracing and channel modeling to predict these dynamic behaviors (Idogho & George, 2022)[5]. Research strives to mitigate the impact of multipath fading using advanced antenna technologies and signal processing techniques (Sulyman et al., 2014)[1].

As device density rises, congestion and interference threaten network performance. Researchers combat these challenges through traffic shaping, frequency reuse, and cell sectorization (Israr et al., 2021)[4]

The complex architecture and software-defined networking reliance of 5G networks amplify security vulnerabilities (Suryavanshi et al., 2020). Proposed security protocols and encryption techniques aim to safeguard against eavesdropping, unauthorized access, and data breaches (Sulyman et al., 2014)[1]. Research concentrates on developing intrusion detection systems and secure key management strategies to counter evolving security threats in 5G environments (Israr et al., 2021)[4].

Accurate path loss prediction emerges as a linchpin for optimizing network performance and resource allocation in 5G (Idogho & George, 2022)[5]. Traditional path loss models may require adaptation for complex environments, prompting exploration into machine learning-based prediction methods (Nguyen & Cheema, 2021)[8]. Precise path loss estimation facilitates efficient cell planning, power allocation, and handover optimization, resulting in enhanced coverage, capacity, and user experience (Phillips et al., 2012)[2].

Weather conditions like rain, fog, and snow exert significant impacts on signal propagation through attenuation and scattering (Banday et al., 2019)[8]. Dynamic path loss models adapting to real-time weather changes are under investigation (Nguyen & Cheema, 2021). Research directs attention towards integrating weather forecasting data into network management systems to proactively adjust transmission parameters and optimize network performance under diverse weather conditions (Israr et al., 2021)[4].

The review elucidates the key challenges faced by 5G wireless communication across multiple dimensions, addressing constraints of higher frequencies and ensuring robust connectivity and security in varied environments. This understanding lays the foundation for future research and development endeavors aimed at achieving reliable and efficient communication in the 5G era.

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~~(PP)The Interplay of Frequency, Path Loss, and Reliable Communication in Diverse Environments~~

~~Higher Frequencies and Millimeter-Wave Bands:~~

~~Dynamic and Diverse Environments:~~

~~Mobile User Mobility:~~

~~Propagation Characteristics:~~

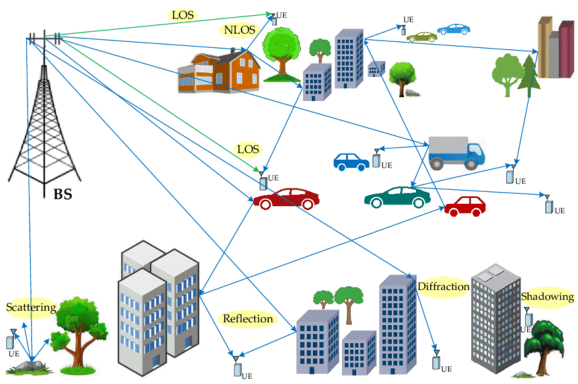
~~Network Congestion and Interference:~~

~~Security Considerations:~~

~~Path Loss Variation:~~

~~Variable Environmental Conditions:~~

2.1 Diagram:



2.3 Signal Impairment and QoS

Significant signal degradation, often manifested as high path loss, negatively impacts Quality of Service (QoS) in 5G networks (Sharma & Singh, 2010). This section explores the detrimental effects of signal impairment on various QoS metrics and highlights ongoing research efforts to mitigate these challenges.

Understanding and mitigating the detrimental impact of high path loss on Quality of Service (QoS) in 5G networks requires a precise grasp of radio propagation. This lies in radio propagation models, mathematical tools that predict signal loss based on factors like distance, frequency, and even environment (Phillips et al., 2012)[2]. Accurate such models are crucial for diverse applications, from planning spectrum usage to optimizing communication in high-mobility scenarios like V2V and nomadic networks.

Phillips

Traditional empirical models, while important for foundational network planning, often struggle with accuracy in complex environments. Analytical models, on the other hand, simplify environmental uncertainties, assuming a single model for the entire link, which may not hold true in large areas with diverse sub-regions. Here, deep learning (DL) emerges as a promising solution. Inspired by computer vision, DL algorithms can adapt to diverse environments, offering context-aware predictions that address the limitations of traditional models. Recent work by Morocho-Cayamcela et al. (2020) exemplifies this potential, showcasing how DL can enhance propagation models for more accurate predictions and efficient network technologies

Diminished signal strength due to path loss, a frequent challenge in 5G networks, introduces vulnerabilities in reliability and increases susceptibility to interference, leading to higher latency (Banday et al., 2019)[8]. This negatively impacts real-time applications like online gaming and video conferencing, and also results in decreased download and upload speeds (Sulyman et al., 2014). Additionally, elevated path loss can induce connection instability, characterized by signal fluctuations, which disrupts user experience and leads to dissatisfaction (Israr et al., 2021)[4].

Further emphasizing the real-world consequences, a recent study in Nigeria by Ekah et al. (2022) investigated the impact of specific weather variables like relative humidity, wind speed, rainfall, and temperature on dropped calls for four major mobile networks. Their findings highlight the irregular patterns in how these tropospheric factors can affect different networks, further illustrating the complexity of signal degradation in real-world environments.

The quest for accurate path loss prediction has taken a leap forward through the application of deep learning, particularly Convolutional Neural Networks (CNNs) empowered by satellite imagery. Compared to traditional models, CNNs demonstrate significant gains, with improvements of around 1 dB at 811 MHz and 4.7 dB at 2630 MHz. Satellite imagery further enhances accuracy by another 1 dB and 0.8 dB, respectively (Thrane et al., 2020).

However, this exciting landscape presents challenges. Selecting and implementing deep learning models can be complex, with factors like model choice and execution time adding layers of difficulty. Expanding the dataset, especially with enriched metadata like satellite images, can significantly improvegeneralizability and quantify the true benefits of these models (Thrane et al., 2020).

Recent research showcases the potential of deep learning to tackle even challenging scenarios. Sung et al. (2023) propose a DNN specifically designed for V2V communication using mmWave frequencies in urban environments. This model seamlessly integrates NLOS situations with large vehicles and variable precipitation, showcasing impressively low statistical errors. This study highlights the potential of deep learning to create robust path loss models for diverse environmental factors, potentially reducing measurement costs and saving time in real-world applications.

Cheng & Cho (2021) contribute another noteworthy example with their AE-CNN model for 5G communications at 28 GHz in suburban environments. Leveraging advanced techniques like dilated convolution and attention mechanisms, their model efficiently predicts path loss, particularly considering the complexities of buildings and streets. While demonstrating the effectiveness of deep learning, the study acknowledges the need for further optimization of network structures and hyperparameters. This resonates with the call for continued exploration of deep learning's potential for path loss modeling across various contexts.

Deep learning offers a transformative approach to path loss prediction, promising significant accuracy gains and efficiency even in challenging scenarios. While hurdles remain in model selection and data needs, ongoing research paves the way for robust and customizable path loss models, ultimately optimizing wireless communication systems across diverse environments.

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2.4 Good Signal Representation

This section explores the significance of robust signal representation in maximizing Quality of Service (QoS) within 5G networks (Banday et al., 2019)[8]. We explore how improving signal strength, low latency, fast data transfer rates, and stable connections can improve network performance and user experience.

Reliable communication is built on the foundation of optimal signal strength. Strong signals provide reliable data transfer and a smooth user experience by reducing the chance of interference and dropped calls (Phillips et al., 2012)[2]. Reliability is further increased by methods like adaptive modulation and coding, which improve signal strength based on current channel circumstances (Sulyman et al., 2014).

Low latency, characterized by minimal delays in data transmission, is critical for real-time applications like online gaming, video conferencing, and virtual reality (Israr et al., 2021)[4].

High path loss and network congestion can contribute to latency issues, impacting the responsiveness and user satisfaction of these applications (Zhou et al., 2022). Strategies like efficient resource allocation and network densification aim to minimize latency by optimizing network resources and reducing transmission distances.

High data transfer rates are essential for both user experience and network performance. Improved streaming experiences, faster content delivery, and more effective data transfer all around are made possible by faster downloads and uploads (Zhang et al., 2021). Improved network protocols and cutting-edge antenna technology offer higher data rates, meeting the needs of bandwidth-hungry apps and improving user experience.

Reliable connections are crucial for a satisfying user experience because they exhibit low signal jitters and dropped calls. Frequent disruptions can be frustrating and hinder seamless communication, particularly in mission-critical scenarios like emergency services and remote healthcare (Israr et al., 2021)[4]. Techniques like beamforming and handover optimization strive to maintain stable connections, ensuring reliable data transmission and user satisfaction.

By understanding the crucial role of good signal representation in various aspects of QoS, we can prioritize research efforts towards optimizing signal strength, minimizing latency, maximizing data transfer rates, and ensuring stable connections. Thus, the door is opened for high-performance 5G networks that will accommodate the increasing demands of data-intensive services and real-time applications while providing outstanding user experiences.

Sangaiah, A. K., Javadpour, A., Pinto, P., Ja'fari, F., & Zhang, W. (2022). Improving quality of service in 5G resilient communication with the cellular structure of smartphones. *ACM Transactions on Sensor Networks (TOSN)*, *18*(3), 1-23.

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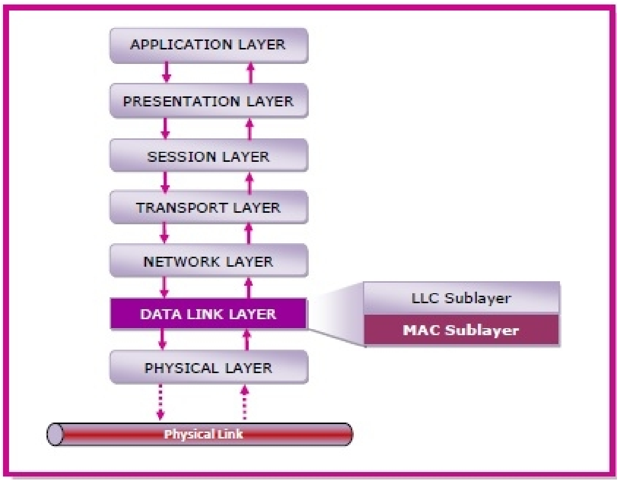
2.5 Concept-Associated Theories Concepts and Supporting Theories of Research "why" and "how"?

Understanding the intricacies of wireless communication involves delving into concept-associated theories. These encompass wireless access, download, upload, retrieval techniques, call quality, transfer speed, network congestion, network inefficiency, inaccurate path loss, network performance, and the intricate relationship between wireless networks and energy consumption rates.

2.5.1 Wireless Access

Concept: The ability to connect to a wireless network and utilize its services like data transfer, voice calls, etc.

Theories: Cellular Access Protocols (MAC protocols). The medium access control (MAC) is a sublayer of the data link layer of the open system interconnections (OSI) reference model for data transmission. It is responsible for flow control and multiplexing for transmission medium. It controls the transmission of data packets via remotely shared channels. It sends data over the network interface card.



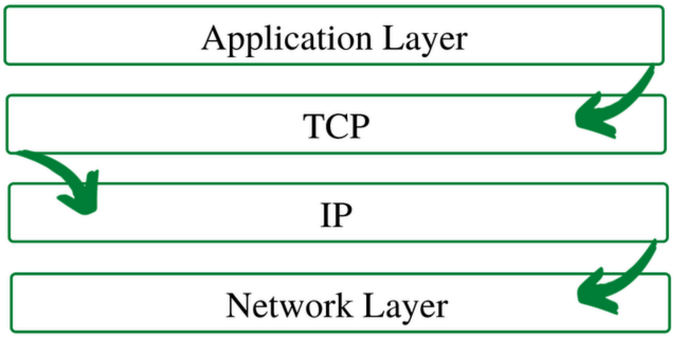
2.5.2 Wireless Download

Concept: Receiving data over a wireless connection, typically from a server to a mobile device.

Theories: Cellular network download speeds (LTE vs. 5G), TCP/IP protocols for data transfer, caching techniques for efficiency.

TCP/IP stands for Transmission Control Protocol/Internet Protocol and is a suite of communication protocols used to interconnect network devices on the internet.

Transmission Control Protocol (TCP) is one of the main protocols of the Internet protocol suite. It lies between the Application and Network Layers which are used in providing reliable delivery services. It is a connection-oriented protocol for communications that helps in the exchange of messages between different devices over a network. The Internet Protocol (IP), which establishes the technique for sending data packets between computers, works with TCP.



2.5.3 Wireless Upload

Concept: Sending data over a wireless connection, typically from a mobile device to a server.

Theories: Upload speeds in cellular networks, buffer management for smooth transfers, data compression techniques.

2.5.4 Wireless Retrieval Techniques

Concept: Locating and accessing specific information or resources within a wireless network.

2.5.5 Wireless Call Quality

Concept: The perceived quality of voice calls made over a wireless network, encompassing factors like clarity, delay, and dropped calls.

Theories:

Signal-to-noise ratio (SNR)

In 1924, AT&T engineer Henry Nyquist recognized that even ideal communication channels have a limited data transmission capacity. Nyquist developed an equation for the maximum data rate in a noiseless channel. In 1948, Claude Shannon expanded Nyquist's work to include channels affected by random noise, making Shannon's paper a cornerstone in information theory.

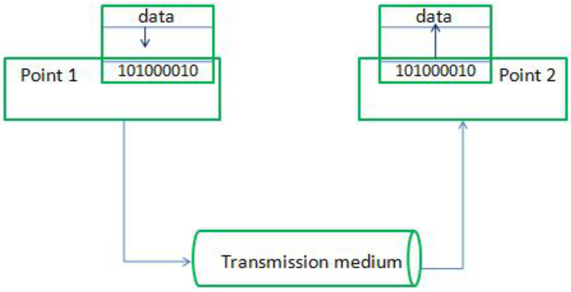
Data rate determines the speed of data transmission, crucial in communication. It relies on bandwidth, digital signal levels, and channel quality. Nyquist and Shannon proposed theoretical formulas to calculate data rate, with Nyquist for noiseless channels and Shannon for noisy ones.

Nyquist's theorem relates the bit rate (BitRate) of a channel to its bandwidth and the number of signal levels (L) used. The equation, BitRate = 2 * Bandwidth * log2(L) bits/sec, highlights that as bandwidth is fixed, the data rate is directly proportional to the number of signal levels.

Shannon's capacity formula, Capacity = bandwidth * log2(1 + SNR), determines the highest theoretical data rate in a noisy channel. Here, bandwidth is fixed, and the channel capacity is directly proportional to the signal-to-noise ratio (SNR), where SNR = (Power of signal) / (power of noise). The SNR, usually expressed in decibels, is given by the formula 10 * log10(S/N)

2.5.6 Transfer Speed

Concept: The data transfer speed or rate is the ratio of digital data moved between two points in a set time. This can be two computers on a network or the transfer between devices like a thumb drive and a hard drive. It measures the speed of data exchange in a network, quantified in bits or bytes per second the rate at which data is transferred over a wireless connection, measured in bits per second (bps).



Transmission of data from one point to another

Theories:

Modulation techniques

Modulation is the process of converting data or information into electrical or digital signals so that those signals can be transmitted across a media while Demodulation is the process of obtaining information or data from the delivered signal.

Types of modulation:

1. **Amplitude Modulation (AM):** Varies the amplitude of the carrier signal to encode data, while keeping phase and frequency constant.
2. **Frequency Modulation (FM):** Alters the frequency of the carrier signal to convey data, with phase and amplitude remaining unchanged.
3. **Phase Modulation (PM):** Changes the phase of the carrier signal to represent data, using different phases for distinct information values.

2.5.7 Wireless Network Congestion

Concept: When demand for network resources exceeds capacity, leading to slower speeds, increased latency, and potential service disruptions.

Theories: Traffic shaping algorithms for resource allocation, load balancing techniques, cell splitting or sectorization for capacity enhancement.

2.5.8 Wireless Network Inefficiency

Concept: When network resources are not optimally utilized, leading to wasted bandwidth, increased power consumption, and suboptimal performance.

2.5.9 Inaccurate Path Loss

Concept: The deviation of actual signal strength from predicted values, impacting coverage, data rates, and overall network performance.

Theories: Traditional path loss models for different environments, limitations of these models in complex scenarios, deep learning techniques for improving prediction accuracy.

2.5.10 Wireless Network Performance

Concept: The overall effectiveness of a wireless network in delivering services to users, considering factors like coverage, speed, latency, reliability, and call quality.

Theories: Key performance indicators (KPIs) for network evaluation, network optimization techniques,quality of service (QoS) mechanisms for prioritized bandwidth allocation.

2.5.11 Wireless Network and Energy Consumption Rate

Concept: The amount of energy required to operate a wireless network, including base stations, mobile devices, and supporting infrastructure.