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Path Loss and Models: A Survey and Future Perspective for Wireless Communication Networks

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ABSTRACT

Modern wireless systems for mobile communication use electromagnetic waves to transmit information over the air, enabling seamless connectivity for a wide range of devices. However, one of the key challenges in wireless communication paths is loss in the strength of propagated signals. Path loss refers to the reduction in signal strength as it propagates through the wireless channel. Path loss models are mathematical representations that capture the attenuation of signal power due to various factors such as distance, frequency, obstacles, and environmental conditions. Understanding and modeling path loss is crucial for designing and optimizing wireless communication systems, as it directly impacts the coverage area, link quality, and overall performance of the network. By accurately modeling path loss, engineers can also optimize various aspects of a wireless communication system, such as antenna placement; transmit power control, and interference mitigation, ultimately improving the broad-spectrum performance and reliability of the network. This paper investigates the concept of path loss in wireless communication networks and provides a comprehensive overview of its various models and their use in designing and implementation of networks. Furthermore, it reviews existing path loss models, and explains their advantages and disadvantages. Finally, it discusses the current trends future research directions related to path loss and its models. The findings in this study can help them better design and implement robust wireless communication networks with improved signal quality and capacity.

Keywords -**Propagated Signals, network performance, fading, Path loss, path loss modeling, Model optimization**

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I. Introduction

Modern wireless communication systems have greatly transformed the way we communicate and interact with one another. With the advancement of technology, wireless communication has become faster, more reliable, and widespread, enabling seamless connections between devices and individuals [1-3]. One key feature of modern wireless communication systems is their ability to transmit large amounts of data at high speeds. This is made possible by developments such as 4G and 5G networks, which allow for faster and more efficient data transmission, enabling activities such as video streaming, online gaming, and cloud computing [4, 5]. In addition, the increased capacity of modern wireless networks ensures that multiple devices can be connected simultaneously, supporting the growing number of devices people use in their everyday lives.
Furthermore, modern wireless communication systems offer enhanced reliability and stability compared to their predecessors. With the integration of technologies such as beamforming and MIMO (Multiple Input Multiple Output), wireless signals can be directed and focused towards specific devices, minimizing interference and optimizing signal quality [5]. This ensures that wireless connections remain stable and robust, even in crowded areas or environments with high interference. Moreover, the development of advanced encryption protocols and security measures has bolstered the security of wireless communication, providing users with secure and private connections. These advancements have made many modern wireless systems for mobile communication a pivotal

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component of various fields, including healthcare, transportation, and entertainment, ensuring seamless transmission of critical information and enhancing the overall user experience.

Generally, the modern wireless communication systems use electromagnetic waves to transmit information over the air, enabling seamless connectivity for a wide range of devices. However, one of the key challenges in wireless communication is the high propagation signal attenuation, leading to huge path loss [4-9]. Path loss refers to the shrinking of transmitted signal, as it propagates through the wireless channel. This loss occurs due to a variety of factors, including distance, obstacles, and interference. As signals propagate through space, they experience attenuation, resulting in a reduction of their strength. This decrease in signal power can be attributed to several phenomena, such as path loss, shadowing, absorption, diffraction, reflection, refraction, and scattering [5-12].

One significant factor contributing to signal path loss is distance [2, 3]. As the signal travels further away from its source, it spreads out and weakens, requiring amplification or regeneration to maintain its integrity. Additionally, obstacles such as buildings, trees, and geographical features obstruct the propagation of the signal, further reducing its strength. These objects block the direct line of sight between the transmitter and receiver, leading to more severe attenuation. Moreover, interference from other sources, such as nearby electronic devices or atmospheric conditions, can also affect signal propagation, resulting in additional losses along the path. Engineers and researchers aim to minimize such losses to ensure reliable and efficient signal transmission

Path loss models are mathematical representations that capture the attenuation of signal power due to various factors such as distance, frequency, obstacles, and environmental conditions. Understanding and modeling path loss is crucial for designing and optimizing wireless communication systems, as it directly impacts the coverage area, link quality, and overall performance of the network [10-20]. By accurately modeling path loss, engineers can also optimize various aspects of a wireless communication system, such as antenna placement; transmit power control, and interference mitigation, ultimately improving the overall performance and reliability of the network.

This paper is timely carried to provide detailed underlying principles that govern signal propagation, the factors contributing to path loss and some key existing models. The current trends and future direction towards the effective development and provision of accurate path loss models is also presented.

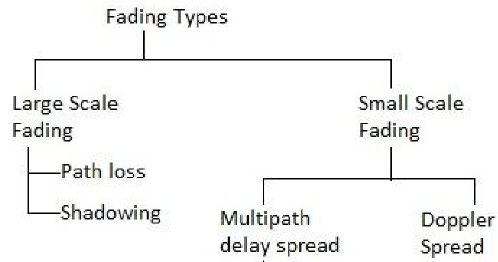

Figure 1: Signal Fading and Types

II. Theoretical Framework

(i) Signal Propagation, Fading and Path loss in wireless communication systems

Signal propagation, fading, and path loss are fundamental concepts in wireless communication systems. Understanding these phenomena is crucial for designing reliable and efficient wireless networks. Signal propagation refers to the behavior of electromagnetic waves as they travel through a medium, such as air or water. Fading is a phenomenon that typically occurs in wireless communication systems and refers to the variation in signal strength or quality [12, 14, 2-25]. There are two foremost fading types: slow and fast fading. Slow fading occurs when the propagated signal shrinks, attenuates and experiences changes in amplitude and phase over a relatively long period of time. This type of fading is mainly caused by obstacles, such as erected man-structures like buildings or natural impediments like trees, all which impede the signal path. Fast fading turbulence, occurs when the signal experiences rapid fluctuations in amplitude and phase. This type of fading is caused by multipath propagation, where the signal arrives at the receiver through multiple paths due to reflections, diffraction, and scattering [26, 27].

Path loss is another key aspect that affects the performance of wireless communication systems [27-32]. It refers to the reduction in signal strength as it travels from the transmitter to the receiver. Various factors contribute to path loss, including distance, frequency, and the surrounding environment. The path loss can be estimated using mathematical models, such as the Friis transmission equation, which takes into account the transmit power, the distance between the transmitter and receiver, and the frequency of the signal.

Path loss is particularly important in designing wireless networks, as it helps determine the coverage area of a transmitter and assists in selecting appropriate signal power levels and antenna heights [24-35].

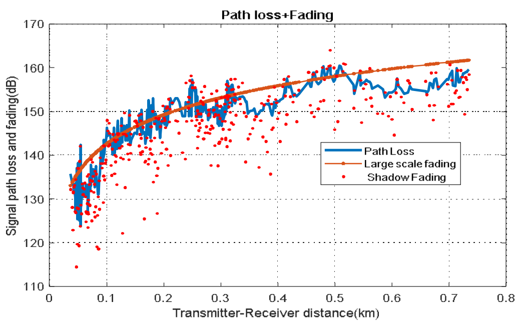

Figure 2: Graphical Representation of Signal Fading and Types

(ii) Shadowing and Fading:

Shadowing occurs due to large obstacles, while fading arises from multipath propagation. Incorporation of statistical models and techniques, such as log-normal shadowing and Rayleigh fading, enhances the accuracy of path loss predictions.

Shadowing involves the process of closely mimicking and imitating a desired behavior, while fading involves decreasing the presence of prompts or supports to promote independent behavior. For example, when teaching a person with a physical disability to use assistive technology, fading could involve gradually reducing the amount of physical guidance provided during the learning process. By gradually removing prompts, the individual becomes more self-reliant and able to perform the target behavior without assistance.

In summary, shadowing and fading are valuable techniques employed in behavior analysis to shape and modify behavior. These methods are particularly effective for teaching new skills and promoting independence in various contexts. Understanding and utilizing these techniques can greatly enhance learning outcomes and facilitate personal growth and development.

(iii). Small-Scale Fading

Small-scale fading phenomenon, also known as multipath fading, is a crucial factor that affects wireless communication systems. It occurs when transmitted signals reach the receiver via multiple paths, resulting in variations in the received signal strength. This phenomenon is caused by the constructive and destructive interference of the signals as they propagate through different paths with different lengths and delays. These variations in the received signal strength can lead to significant signal fluctuations and distortions, making it challenging to maintain reliable and high-quality communication links.

Understanding small-scale fading is essential for designing and implementing wireless communication systems. One of the main causes of small-scale fading is the presence of obstacles and reflecting surfaces in the propagation environment. As the transmitted signals bounce off these objects and propagate through different paths, they encounter phase shifts and amplitude changes, which can lead to severe signal attenuation or enhancement at the receiver. To mitigate the effects of small-scale fading, various techniques can be employed, such as diversity schemes, equalization, and interference cancellation strategies. By characterizing and comprehending small-scale fading phenomena, researchers and engineers can develop efficient techniques to enhance the performance and reliability of wireless communication systems, ultimately advancing the field of wireless communication technology.

(iv). Large Scale Fading

As signals propagate through the wireless medium, they are subject to various forms of fading due to factors such as path loss, shadowing, and multipath propagation. Large-scale fading specifically refers to the variation in signal strength over distances on the order of hundreds of meters to kilometers. This phenomenon occurs primarily due to path loss, which leads to a decrease in signal power as it travels away from the transmitting source [28]. Understanding and characterizing large-scale fading is of utmost importance in designing and optimizing wireless systems, as it directly impacts signal coverage, capacity, and quality of service.

One key aspect of large-scale fading is path loss, which refers to the attenuation of signal power as it propagates through space. This phenomenon is primarily caused by the spreading loss, which occurs due to the expansion of the signal wavefront as it travels away from the source. Additionally, shadowing, a form of large-scale fading, occurs due to physical obstructions such as buildings, structures, or natural terrain, which block or scatter the signal, leading to variations in signal strength. Moreover, multipath propagation further exacerbates large-scale fading by causing constructive or destructive interference of the signal, resulting in significant fluctuations in signal strength at different locations In order to mitigate the detrimental effects of large-scale fading, wireless communication systems employ techniques such as power control, diversity, and adaptive modulation to ensure robust and reliable operation.

Understanding and mitigating large-scale fading is essential for the design and optimization of wireless networks. By characterizing the fading conditions, network engineers can implement techniques like power control, antenna diversity, and adaptive modulation to ensure reliable connectivity and efficient resource allocation [29-33]. Additionally, advanced signal processing algorithms such as equalization and channel coding can be employed to combat the effects of large-scale fading, further enhancing the overall system performance.

Considering the significant impact of large-scale fading on signal coverage, capacity, and quality of service, researchers and engineers must continue to develop innovative techniques to mitigate its effects and improve wireless communication systems.

III. Materials and Methods

Generally, Signal path loss models are mathematical equations used to describe the attenuation or weakening of a signal as it travels through a medium or path [34-40]. These models provide a quantitative understanding of how a signal's strength diminishes with increasing distance, interfering objects, or various environmental factors.

This section provides a comprehensive overview of its various models and their use in designing and implementation of networks. Furthermore, it reviews existing path loss models, and explains their advantages and disadvantages**.** Finally, it discusses the current trends future research directions related to path loss and its models. The findings in this study can help them better design and implement robust wireless communication networks with improved signal quality and capacity.

(i). Frequency Dependent Path Loss Models

Frequency dependent path loss models are a crucial aspect of wireless communication systems as they provide accurate predictions of signal attenuation at different frequencies. These models take into account the physical characteristics of the environment, such as buildings, trees, and terrain, which affect the propagation of wireless signals. By considering the frequency dependence of path loss, these models can accurately estimate the signal strength and coverage area of a wireless network. Table 1 provides some information on other parameters of popular Frequency dependent path loss models.

One commonly used frequency dependent path loss model is the Hata-Okumura model [36-40]. This model takes into account the distance between the transmitter and receiver, as well as the height of the antennas, to estimate the path loss at different frequencies. The Hata-Okumura model can be further adjusted based on the type of environment, such as suburban or urban areas, to provide more accurate predictions. Another widely used model is the COST-231 model which considers the frequency, distance, and height of antennas, as well as the clutter loss caused by buildings and vegetation. Models such as ITU-R P.1238 provide a systematic approach to estimate frequency-dependent path loss, considering factors like urban morphology, transmissions below and above roof level, and varying propagation conditions across frequency bands.

Frequency Dependent Path Loss Models are essential for the planning and optimization of wireless networks. By accurately predicting the signal strength and coverage area, these models help network designers determine the optimal placement of base stations and antennas to ensure efficient and reliable communication [38-50]. Moreover, they assist in the design of wireless communication systems in areas with varying frequencies, such as hospitals, airports, and urban centers, where multiple services are provided simultaneously. Overall, frequency dependent path loss models play a crucial role in the advancement and improvement of wireless communication systems.

(ii). Free Space Path Loss (FSPL) Model:

FSPL represents the path loss incurred in ideal conditions with no obstacles or interference. Thus, the FSPL model assumes an ideal environment with no obstacles, reflections, or interference, making it a valuable tool for initial signal strength calculations. The model calculates the power loss between a transmitter and a receiver by considering factors such as the distance between them, the frequency of the signal, and the characteristics of the antennas used. This model serves as a foundation for more complex path loss models that consider additional factors such as the influence of obstacles or multipath fading.

It provides a mathematical relationship between the power transmitted, the gains of the transmitting and receiving antennas, the wavelength, and the distance between them. The FSPL model is mathematically represented as [41, 42]:

$$LF=P_t/P_r = (4\pi d)^2/G_t\, G_r\lambda^2\} = (4\pi fd)^2/GtGrc^2 \quad (1)$$

where,

P_r = Receive power

P_t = Transmit power

d = Transmitter-Receiver distance

λ = wavelength

c = speed of light

G_r = receiver antenna gain

G_t = transmitter antenna gain

f=Transmit Frequency

This model indicates that the power received diminishes with the square of the distance, emphasizing the importance of maintaining minimal distances between the antennas to maximize the signal strength. Moreover, it highlights the significance of antenna gains, implying that by increasing the gain of either the transmitting or receiving antenna, the overall power received can be enhanced.

(iii) Okumura-Hata Model:

The Okumura-Hata model equation is a widely used empirical formula that predicts the path loss of radio waves in the urban environment. Originally developed by Japanese researchers Okumura and Hata, this equation takes into account various factors such as frequency, distance, base station height, and antenna height, to estimate the signal strength at a particular location. The model accounts for both line-of-sight and non-line-of-sight transmission, making it a valuable tool for designing and optimizing wireless communication systems in urban areas [40-46].

The equation itself is a weighted sum of several components, including free space loss, diffraction loss, and penetration loss. The free space loss factor accounts for the attenuation of the signal as it

Volume: 15 Issue: 02 Pages: 5892– 5907 (2023) ISSN: 0975-0290

propagates through space, assuming no obstacles or reflections. On the other hand, the diffraction loss factor considers the impact of obstacles such as buildings or terrain irregularities on the signal. Lastly, the penetration loss component takes into account the attenuating effect of building materials on the radio waves. These factors are combined to provide an estimation of the path loss, allowing engineers to predict and optimize the coverage area and quality of wireless networks in urban environments.
By considering various factors influencing signal propagation, this equation enables engineers to make intelligent decisions regarding antenna placement, coverage area, and overall system performance. Through its widespread use and reliable results, the Okumura-Hata model equation continues to benefit the telecommunications industry and advance wireless communication technologies.

(iv). Cost 231 Hata Model

The Cost 231 Hata model extends the Okumura-Hata model by integrating additional parameters such as rural, suburban, and open area environments. By incorporating an innovative correction factor, this model provides greater accuracy in predicted path loss values.
The Cost 231 Hata model is a widely-used empirical propagation model in the field of telecommunications. Developed by the European Telecommunications Standards Institute (ETSI), it provides a means to estimate the path loss in urban areas, taking into consideration various influencing factors such as frequency, distance, antenna height, and environment. The model is particularly valuable for predicting signal strength between a transmitter and receiver, which is essential for network planning and optimization.
This model takes into account the complex propagation mechanisms that occur in urban areas, where signals encounter obstacles like buildings, trees, and other obstructions. By considering the height of both the transmitting and receiving antennas, the frequency of operation, and the distance between the antennas, the Cost 231 Hata model provides a reliable estimate of path loss. The model also includes adjustments for different types of terrain and clutter, allowing for more accurate predictions in varying environmental conditions [3, 30]. As a widely-accepted and extensively-used model, it has been instrumental in the design and optimization of wireless communication systems in urban environments, contributing to more efficient network planning and improved communication services.

Table 1: Some Popular Path loss Models, and their Correction Factors

Model	Pathloss Formula and Antenna Correction Factors
Free space	$PL(dB) = 20log10\left(\frac{4\pi Rf}{C}\right) = 20log10(R) + 20log10(f) + 20log10\left(\frac{4\pi}{C}\right)$
Walficsh-Bertoni(W/B)	$PL_{total} = \left(\frac{\lambda}{4\pi R}\right)^2 P(g)^2 \frac{\lambda\rho_1}{2\pi^2(H_b - h_m)} = \frac{5.51}{32\pi^4}\frac{(h_r - H_g)^{1.8}\rho_1 d^{0.9}}{(H_B - h_m)^2}\frac{\lambda^{21}}{E^{3.8}}$ $PL_{total}(dB) = 89.5 - 10\log\left[\frac{\rho_1 d^{0.9}}{(H_B - h_m)^2}\right] + 21\log f_m - 18\log(h_T - H_B) + 38\log R_k$ $\rho_1 = \sqrt{\left(\frac{d}{2}\right)^2 + (H_B - h_m)^2}$
SUI	$PL_{total}(dB) = A + 10n\log_{10}\left(\frac{d}{do}\right) + X_f + X_b + S \quad for \quad d > do$ $A = 20\log_{10}\left(\frac{4\pi d_o}{A}\right)$, $n = a - bh_b + C/h_b$, $X_f = 6.0\log_{10}\left(f/2000\right)$, $X_h = -10.8\log_{10}\left(\frac{hr}{2000}\right)$
COST-231(W/B)	$PL_{total}(dB) = L_0 + L_{rts} + L_{msd}$, where $L_0 = 32.44 + 20logf + 20logd$, $L_{rts} = -16.9 - 10logw + 10logf + 20logh_{roof} - h_{RX} + Lor_1$, with $Lor_1 = 4.0 - 0.114(\phi - 35$, $L_{msd} = L_{bsh} + K_a + K_d logd + K_f logf - 9logb$, with $L_{bsh} = -18(1 + h_{Tx} - h_{roof})$.
ECC	$PL_{total}(dB) = A_{fs} + A_{bm} - G_b - G_r$, $Afs = 92.4 + 20log(d) + 20log(f)$, $Gr = 42.57 + 13.17log(f)][log(h_{MS}) + -0.585]$, $G_b = log10(h_b/200)\{13.958 + 5.8[log(d]^2\}$ $Abm = 20.41 + 9.83log(d) + 7.894log(f) + 9.56[log(f]^2$
Egli	$PL_{total}(dB) = 20\log_{10}fc + 40\log_{10}R + 20\log_{10}hbs + 76{:}3 - 10\log_{10}hms$
Lee	$PL_{total}(dB) = 10n\log(d) - 20\log(h_{BS}) - P_o - 10\log(h_{MS}) + 29$
Hata	$PL_{total}(dB) = A + B\log10(f) - 3.82\log10(h_{BS}) - a(h_{MS}) + [C - 6{:}55\log10(h_{BS})]\log10(d) + C_m$,with A=69.55,B=26.16 for f=(150-1000)MHz and A=46.3,B=39.9 for f=(1500-2000)MHz

(v). Hybrid Path Loss Models

Hybrid models combine empirical and theoretical approaches to path loss estimation. These models account for the unique characteristics of different environments and use a combination of statistical analysis, measurements, and propagation predictions to generate accurate results across various scenarios. Hybrid path loss models are an advanced approach used in wireless communications to estimate the attenuation of a signal as it propagates through a medium. Mixing both empirical measurements and theoretical analyses, these models aim to provide more accurate predictions of signal strength, enabling better network planning and optimization. By combining the strengths of both empirical and theoretical models, hybrid path loss models can overcome the limitations of individual models, leading to improved performance in wireless communication systems [38, 39, 41].

The empirical component of hybrid path loss models involves collecting real-world measurements of signal strength at various locations. These measurements are then used to capture the power attenuation caused by obstacles, interference, and other environmental factors. On the contrary, the theoretical component employs mathematical equations to describe the signal propagation characteristics. This includes considering parameters like frequency, distance, antenna height, and path loss exponent. By integrating empirical data with theoretical models, hybrid path loss models can provide more accurate estimations for specific scenarios that may not be fully captured by either empirical or theoretical models alone. This hybrid approach ensures that the path loss predictions are not only realistic but also adaptable to varying environments and wireless communication systems.

(vi). Advanced Path Loss Models:

Advanced path loss models, such as those based on ray tracing [45 and radio wave simulations, offer highly accurate path loss prediction capabilities in complex scenarios. These models account for detailed information on terrain, building materials, object interactions, and diffraction effects, enabling more precise wireless system design and network planning [45-49].

Advanced path loss models are an essential tool in the field of wireless communication as they provide accurate predictions of signal propagation. With the advent of new technologies and the increasing complexity of communication systems, traditional models fail to capture the intricate nature of signal propagation. Advanced path loss models take into account various factors such as antenna height, frequency, terrain, and building characteristics to provide a more comprehensive understanding of signal strength at different locations. These models leverage advancements in mathematical algorithms and statistical methods, allowing for more accurate predictions and optimization of wireless networks.

One example of an advanced path loss models includes the Ray tracing model, Walficsh-Bertoni model and Okumura-Hata model [50, 51], which takes into consideration the effect of distance and terrain on signal propagation. This model incorporates parameters such as base station height, mobile station height, and frequency to estimate the path loss. Another model, the COST 231 Hata model, builds upon the Okumura-Hata model by including additional factors such as street orientation and urban clutter. By incorporating these advanced models, network planners and operators gain a deeper understanding of signal propagation characteristics, enabling them to make informed decisions regarding the deployment and optimization of wireless networks [42-44].

In conclusion, advanced path loss models play a crucial role in the design and optimization of wireless communication systems. These models provide a more accurate depiction of signal propagation by considering various factors that affect signal strength. As technology continues to advance, the need for advanced path loss models becomes increasingly important to ensure optimal network performance and coverage.

(vii) Advantages and disadvantages of existing path loss models

Existing path loss models play a crucial role in wireless communication system design and optimization [40, 45-50]. These models predict the attenuation of signals as they propagate through a medium, aiding engineers in estimating the quality and coverage of wireless links. One major advantage of these models is their ability to provide a quantitative understanding of signal strength variation with distance, allowing for effective network planning. Additionally, path loss models also facilitate interference analysis, determining the impact of neighboring transmitters on the desired received signal. By considering factors such as terrain, building structures, and foliage, these models can assist in optimizing network performance and minimizing interference.

However, existing path loss models have a few disadvantages that need to be acknowledged. Firstly, these models are often generalized and may not accurately represent specific environments or scenarios [51-60]. As a result, their predictions may have limited accuracy and lead to potential problems in practical implementation. Additionally, path loss models typically assume ideal conditions and do not account for dynamic phenomena such as fading, shadowing, and multipath propagation. These factors can significantly impact signal reception and quality, hence the need for further refinements and extensions to the existing models. Therefore, while path loss models offer valuable insights into wireless communication systems, it is essential to use them with caution and consider their limitations in real-world deployments [55-59].

Volume: 15 Issue: 02 Pages: 5892– 5907 (2023) ISSN: 0975-0290

(viii) Current Trends in path loss model Developments

Accurate Path loss modeling continues to face challenges related to the evolving wireless communication technologies, the increasing demand for higher data rates, and the emergence of new propagation scenarios. There are several current challenges in the development of these models. Firstly, modeling path loss in real-world environments is complex due to the presence of obstacles, such as buildings, trees, and other structures, which can cause signal attenuation and reflection. Developing accurate models that can capture the impact of these obstacles on the radio signals remains a challenge. Additionally, path loss models need to be adaptive to different frequencies and propagation environments. This requires incorporating various factors, such as the environment type, the frequency range, and the characteristics of the wireless devices, into the model. Designing models that can account for all these factors and accurately predict path loss is a challenging task for researchers in this field.

Another challenge in path loss model development is the need to incorporate advanced technologies and techniques [6]. With the advent of 5G and upcoming communication systems, path loss models need to be updated to incorporate the characteristics of these technologies, such as massive multiple-input multiple-output (MIMO) systems and millimeter-wave communication. These advanced technologies introduce new propagation phenomena and require more sophisticated models to accurately estimate the path loss. Additionally, the increasing densification of wireless networks and the deployment of small cells necessitate developing models that can capture the effects of interference and varying transmit powers on the path loss. Therefore, incorporating these advanced technologies and novel techniques into path loss models is a significant challenge for researchers and engineers in this field.

IV. Path Loss Propagation Measurements

Validation and calibration of path loss models require extensive field measurements to assess the accuracy of predicted path loss values. These measurements involve gathering data on signal strength, distance, transmitter location, and environmental factors using specialized equipment and techniques [6, 50, 55, 60-75].

Path loss propagation measurements are typically performed by transmitting a known signal from a fixed location and measuring the received signal strength at various locations within the coverage area. These measurements provide empirical data that can be used to develop accurate path loss models for a specific environment, such as urban, suburban, or rural areas. By accounting for factors like antenna characteristics, frequency, and environmental obstructions, these measurements enable the estimation of path loss and subsequently aid in the design and optimization of wireless networks.

Moreover, path loss propagation measurements also play a significant role in the deployment of wireless systems in both indoor and outdoor environments. In indoor scenarios, measurements are conducted to evaluate signal attenuation caused by walls, ceilings, and other objects. By performing these measurements, engineers can determine the ideal placement of access points and ensure optimal signal coverage throughout the building. Additionally, for outdoor deployments, path loss measurements help identify potential coverage gaps and enable engineers to find optimal locations for base stations or access points. Accurate measurements of path loss also contribute to the efficient allocation of radio resources and power usage, leading to improved overall network performance and user experience. Therefore, path loss propagation measurements are a fundamental tool in wireless communication engineering, providing the necessary data to design and optimize networks for various environments and deployments.

V. **Computation and Analysis of some existing path loss models in Matlab Environment**

This section focuses on the computation, estimation and analysis of some selected key existing path loss in Matlab computational software environment. The selected models include the Free space model, SUI, Okumura Hata model, Walcfisch-Betoni Model and Ericson Model. Specifically, we investigated the selected models in terms of their influencing estimation parameters, and also compare their total loss effects in different signal propagation environments. Figures 3-5 show the performance comparison of Free space model, SUI, Okumura Hata model, Cost 231 Hata and Ericson Model at 900MHz, 1800MHz and 2600MHz transmission frequencies. From the results, the Okumura Hata and Cost 231 Hata attained the highest path loss values; the Free space models provided the lowest path loss values. Figure 6 shows the Hata model performance for different Antenna heights in different signal propagation environment. Figure 7 shows the Hata model performance for different transmission frequencies in different signal propagation environment. Figures 8 and 9 show the Walficsh-Bertoni model performances at different Roof top heights and building separations values. Shown in figures 10 and 11 are antenna heights and frequency dependence of Walficsh-Bertoni model at 2600MHz frequency. Figures 12-14 display the Hata and Walficsh-Bertoni model performance at frequency and heights of the transmission antennas. From the results, Hata model attained higher losses compared to the Walficsh-Bertoni model.

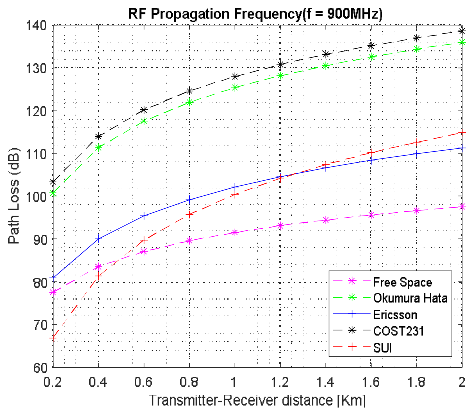

Figure 3: Comparison of Five different Path loss model at 900MHz

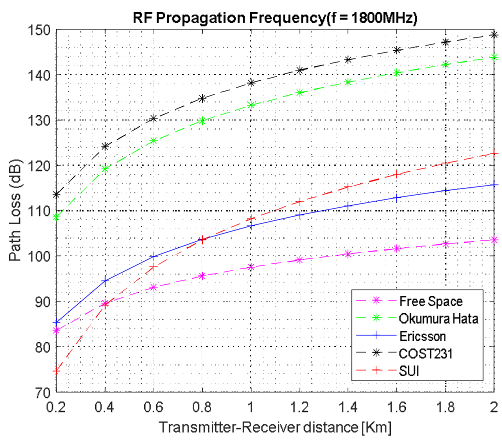

Figure 4: Comparison of Five different Path loss model at 1800MHz

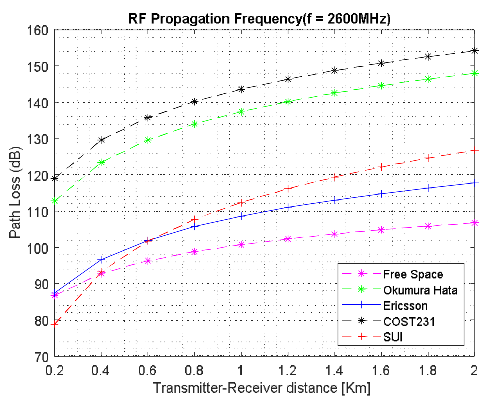

Figure 5: Comparison of Five different Path loss model at 900MHz

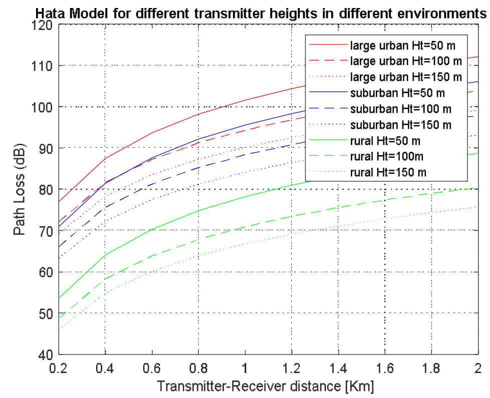

Figure 6: Hata model performance for different Antenna heights

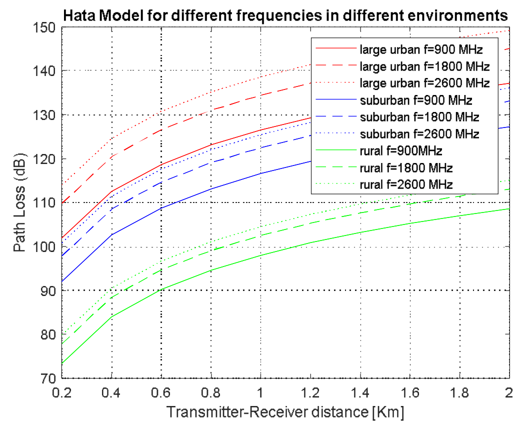

Figure 7: Hata model performance for different Antenna heights

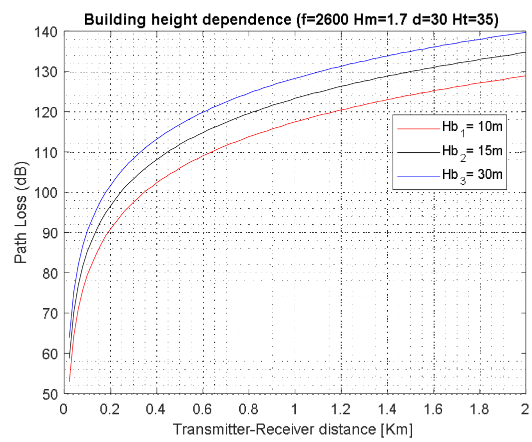

Figure 8: Walficsh-Bertoni model performance for different Roof top heights

Volume: 15 Issue: 02 Pages: 5892– 5907 (2023) ISSN: 0975-0290

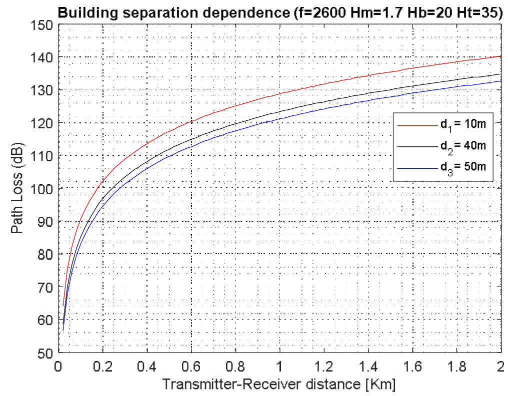

Figure 9: Walficsh-Bertoni model performance for different Building separation

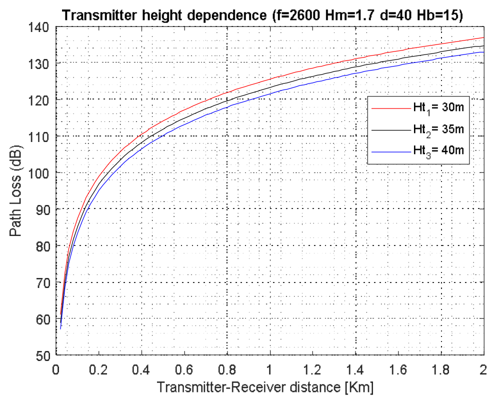

Figure 10: Walficsh-Bertoni model performance for different Antenna Heights

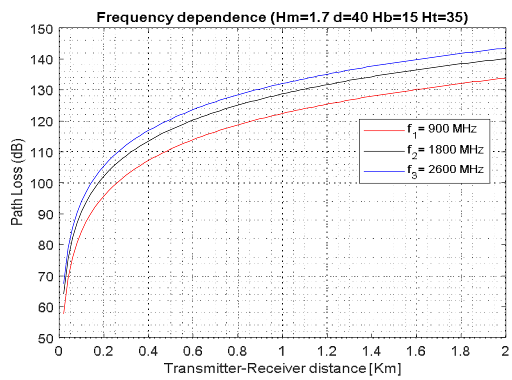

Figure 11: Walficsh-Bertoni model performance for different Frequency

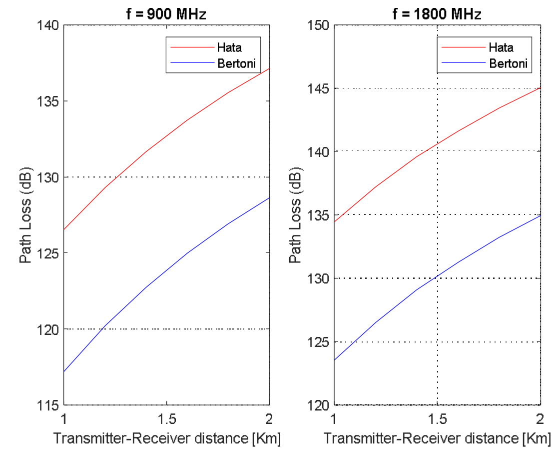

Figure 12: Hata and Walficsh-Bertoni model performance at 900 and 1800MHz

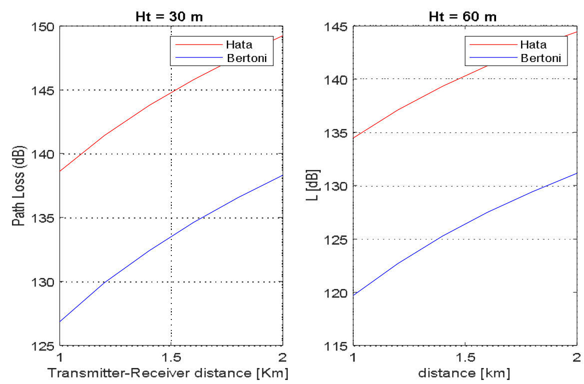

Figure 13: Hata and Walficsh-Bertoni model performance at different antenna Heights

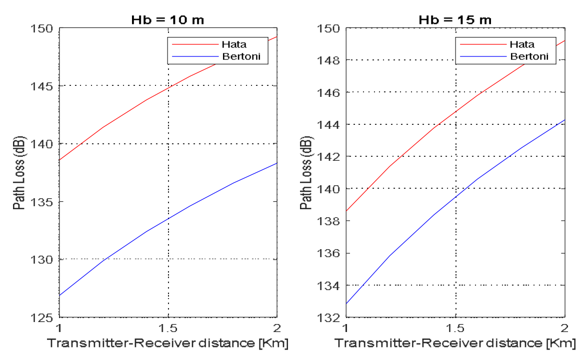

Figure 14:Hata and Walficsh-Bertoni model performance at different heights

VI.Ways and techniques to improve existing path loss models

Existing Path loss models are often limited by their inability to accurately account for real-world factors, leading to discrepancies between predicted and actual signal strength [60-74]. In order to improve existing path loss models, several techniques and approaches can be adopted. Firstly, incorporating advanced propagation technology such as multiple-input multiple-output (MIMO) can enhance the accuracy of path loss models. MIMO systems utilize multiple antennas at both the transmitter and receiver, allowing for spatial diversity and improved signal quality. By incorporating MIMO technology into path loss models, the impact of antenna configurations and spatial characteristics can be better accounted for, leading to more precise estimations of signal attenuation.

Another way to improve existing path loss models is by employing machine learning algorithms [41, 46]. With the aid of AI techniques, path loss models can overcome limitations caused by static assumptions and instead learn from real-world data to make accurate predictions. Machine learning algorithms can extract patterns, relationships, and nonlinearities from extensive datasets, enabling path loss models to adapt and adjust their estimations based on different environmental conditions. By training the models on comprehensive datasets that include various scenarios, such as urban or rural environments, and considering factors like street layouts, building structures, and vegetation density, machine learning can significantly enhance the accuracy of path loss models and provide more reliable estimates of signal attenuation in practical scenarios [41,56].

Though there exist many machine learning-based path loss modeling and predictive studies in literature [4, 10, 20, 770-80], their full practical integration and implementation into the present and future cellular network planning process in yet to be realized. This key challenge is a call for attention and urgent solution.

VII. Future direction in path loss model Developments

As technology continues to evolve, it becomes imperative to explore new directions for path loss model development to address the challenges posed by emerging communication mechanisms and environments [74-80]

One future direction in path loss model development is focusing on millimeter-wave (mmWave) frequencies and implementation. With the growing demand for higher data rates and the scarcity of available spectrum, mmWave bands have gained attention due to their wide bandwidth. However, mmWave signals suffer from higher path loss compared to traditional microwave frequencies due to increased atmospheric absorption and higher penetration losses. Hence, there is a need for accurate path loss models tailored specifically for mmWave frequencies. Future developments in this area could include extensive empirical measurements for mmWave frequencies in various environments to derive accurate and reliable path loss models that can be used for system design and analysis.

Another future direction is incorporating machine learning techniques into path loss model development. Traditional path loss models rely on simplified models based on deterministic assumptions and empirical measurements. However, by leveraging the vast amount of data available from wireless networks, machine learning algorithms can potentially learn more realistic and accurate path loss behavior. These algorithms can analyze large-scale data sets from multiple sources, such as radio frequency fingerprinting, geographical features, and network parameters, to provide more robust models. This would enable network planners and designers to improve the performance and efficiency of wireless communication systems by incorporating machine learning-based path loss models [6, 78-80].

In conclusion, the future direction in path loss model development involves exploring the challenges posed by mmWave frequencies and integrating machine learning techniques. By advancing path loss models tailored for mmWave frequencies and leveraging machine learning algorithms, researchers can develop more accurate and reliable models to address the complexities of modern wireless communication systems. These developments will not only contribute to the design and optimization of communication networks, but also enable the realization of future technologies such as 5G and beyond.

VIII. Conclusion:

In modern wireless communication networks, accurate estimation of path loss is crucial for efficient resource allocation and management. Path loss models and formulas are essential tools for designing and optimizing wireless communication systems. Their accurate modeling and implementation enables engineers to overcome signal degradation, plan efficient network deployments, and improve overall system performance. By continually advancing these models through research and innovation, researchers can unlock new possibilities for wireless communication in a rapidly evolving technological landscape.

However, most existing Path loss models assume a simplified environment and neglect crucial factors such as the surrounding terrain, vegetation, and building structures. To address the limitations of existing path loss models, future research should strive to develop more robust and accurate models that consider the impact of different environment types and propagation mechanisms. Incorporating advanced techniques such as machine learning, channel sounding, and ray tracing simulations can enhance the performance of these models and allow for more accurate predictions. Additionally, studies focusing on the optimization of model parameters, particularly for specific environments or frequency bands, are necessary to improve the accuracy and practicality of path loss models.

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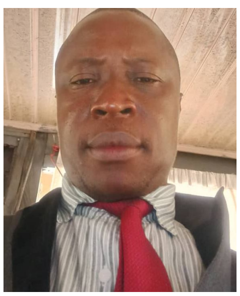

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