ISSN: 2182-2069 / E-ISSN: 2182-2077

Channel Modeling for Internet Services in High-Rise Urban Areas

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Received: June 06, 2025; Revised: July 19, 2025; Accepted: August 16, 2025; Published: August 30, 2025

Abstract

As society becomes increasingly dependent on high-speed online services, the demand for robust and reliable wireless connections in densely populated urban areas, such as tower blocks, has become urgent. In these environments, buildings, elevations, blocked sight lines, and scattered reflections scramble radio waves in ways that simple free-space equations cannot foresee. Channel models provide engineers with a virtual test bed to estimate behavior, guiding them toward cost-effective antenna and cable placements. This work presents a hybrid framework that combines field measurements with physics-based simulations to address the unique challenges presented by high-rise skylines. Core inputs include site-specific data on wall losses, window reflexivity, and vertical diffusion between floors, all distilled into a single parametric engine. A modular architecture is added, allowing users to refine settings on the fly as new observations arrive. When compared to live network probes, the approach reduces path-loss errors by up to thirty percent and enhances coverage maps significantly beyond standard defaults. Because it is platform-agnostic, the model

Journal of Internet Services and Information Security (JISIS), volume: 15, number: 3 (August), pp. 704-717.
DOI: *10.58346/JISIS.2025.I3.047*

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can support 5G, Wi-Fi, and narrowband IoT alike, streamlining rollouts for service providers. These results show a promising bridge between academic theory and the on-the-ground realities of multi-story city living. The results provide valuable insights that can inform future work on city-level messaging networks and smart building design.

Keywords: High-rise Environments, Wireless Signal Propagation, Hybrid Channel Modeling, Simulation and Measurement, Urban Connectivity, 5G and IoT, ISP Planning.

1 Introduction

1.1 Overview of Channel Modeling for Internet Services

These findings provide an encouraging point of contact between theory and practice on the ground in the lives of multi-story cities. The findings can give important directions that can be used in future research on urban level messaging networks and intelligent building design. Channel modeling is at the core of the current wireless systems and with its help, engineers can predict the behavior of signals in different weather conditions, moving traffic, or in the street of a busy city. This method combines math and on-site testing to map the travel, bouncing, and rounding corners, and scattering of radio waves around small scatterers (Kokkoniemi et al., 2021; Faruk et al., 2021; He & Ai, 2024). With an urban network of this scale, with 5G, Wi-Fi 6, and an increasingly growing array of IoT devices, there is a rapid increase in the necessity of models that are finely realistic (Farahani et al., 2018; Alliance, 2016; Sathya, 2023). Full-bodied models provide designers with the melodies they require to cram spectrum even with providing clear high-quality service (Kassim, 2017; Abdullah, 2020; Balta & Özçelik, 2018). However, in dense neighborhoods, a signal can be drowned by interference, path loss, and multipath hence simple theories are seldom true. Due to this fact, a model of trusted channels forms the basis of all the network simulations, cell and access-point strategy and determines the adjustment of hardware (Eller et al., 2022). The new workflows harmonised the data of live drive-tests and high-fidelity simulation and scale up the accuracy that is achieved by the scope of the methods that are only theoretical or measurement-based.

1.2 Significance of the Channel Modeling in the High-rise Cities

The behavior of the wireless signals in an urban setting of a high-rise building is vastly different than that of the fields due to many factors that include building shapes and urban topography. The conventional horizontal propagation traditional models fail to address the complications that are presented by the vertical heights of certain floors in high-rise buildings. Multipath, path loss and vertical diffusion are also critical factors in this regard that influence signal behavior.

- Multipath is a phenomenon that appears with radio waves: the waves reflect off of surfaces such as windows, walls, metal walls, etc. and thus, the receiver receives the same signal several times, but at different times. This can cause positive or negative interference which skews the quality of the signals.
- The fact that it is degraded when traversing space characterizes path loss. The loss is also enhanced by the utilization of materials like concrete and glass that either block or reduce the radio waves in the high-rise structures that emit a larger number of radio waves around or through the walls or the floors.

- Diffusion occurs vertically whereby the signals pass through a building that is spread through the floors. This scattering effect by structural components like floors slabs, ceilings and walls leads to discontinuity of the direct line of the signal and this causes a deviation in the strength of the signal at other levels of the building.

This is essential to model and comprehend these effects so as to create reliable wireless networks in skyscrapers. Correct channel models taking into consideration such factors enable engineers to estimate signal strength, reduce interference, and maximize network coverage on various floors, and have a high rise building fitted with effective and powerful wireless communication networks. This study presents a new hybrid model for radio channels in tall cities, merging elements from flat-ground and rooftop environments to overcome their blind spots.

Section 1, the Introduction, explains why precise wireless maps are important above street level and how height, glass facades, and wind towers affect ordinary forecasts. The second chapter reviews existing approaches and shows that few capture vertical floor-to-floor leaks in signal strength. In Section 3, the Proposed Method, the paper outlines a fusion of drift simulations, live probes, flow processing, and self-tuning layers that together produce sharper vertical snapshots. Results in Section 4 test the framework against real campaigns and illustrate gains with flow diagrams, zone sketches, 3D city grids, and stacked column plots. Section 5, the Conclusion, summarizes key discoveries and advises Internet providers, green architects, and city designers on using the model for future networks in skyscraper districts. The aim is therefore twofold: deepen theory and deliver a tool that can scale with the next vertical wave of urban growth.

2 Related Work

Accurate channel modeling in high-rise urban areas is essential to building reliable, cost-effective wireless networks (Shi et al., 2025). Researchers have widely adopted deterministic techniques, particularly ray-tracing algorithms, to simulate how radio waves propagate through dense clusters of buildings. These tools track reflections, diffractions, and scatterings, phenomena that dominate signal paths inside narrow streets and around tall façades. To refine these forecasts, several studies incorporate height-dependent path-loss formulas that account for how power fades differently on rooftops, balconies, and street canopies. By merging precise 3D geometry with real-time wave behavior, newer modeling platforms now guide site planners toward stronger and more uniform coverage at every height in crowded cities (Arora, 2024; Luo et al., 2020).

Stochastic models have become the go-to choice because they are both flexible and computationally efficient. By extracting statistical parameters directly from measured signals, these models accurately capture how radio waves behave within mixed-use towers. It is a logical step to add floor-specific loss and material penetration and corridor mobility to a three-dimensional framework. It has been reported in close to a hundred studies that hybrid models-stochastic trends coupled to site-specific calibration-can be significantly superior to standard flat-path models. These advantages are especially valuable in planning networks in smart buildings that accommodate populations of a variety of devices and continuously changing occupants.

New work also uses artificial intelligence to simplify the channel modelling and instead of offline prediction, channel modelling has to be adjusted on the fly. Machine-learning engines, trained on city-wide cars on the road tests, have estimated channel state information (CSI), shadowing, and multipath propagation, and floors-by-floors effects Sahadevan & Manikandan, 2017. Beam patterns in the high-rise rapidly changing high rise are also predicted and steered using deep networks. The adaptive systems can modify settings of human flows, gadget clusters, and peak and off-peak timestamps using feedback loops (Cheng & Wei, 2025; Yan et al., 2024). This more intelligent and finer modeling has shown strong profit in trials in densely populated urban places with high-rise buildings (Stevovic et al., 2018; Muller & Romano, 2024; Muller & Romano, 2024). Recent work in joint sensing and network smarts has advanced the concept of real-time, self-tuning channel models (Keliwar, 2023). Sensor clusters built into smart buildings track changes that govern signal path such as warm air, damp floors, or moving furniture and report them continuously. The steady stream of feedback enables ultra-low-latency apps to stay agile, as controllers can adjust power, codes, or slots on the fly. Researchers also test edge servers that handle this data in real-time, thereby shrinking the gap between observation and model update (Hossain et al., 2023). Together, these tools promise to meet the heavy demands of AR/VR and cloud gaming in crowded city towers.

Side-by-side trials of various radio systems within high-rises reveal that each band presents a distinct picture of propagation. Mm Wave waves, for example, lose strength behind floor slabs and glass, while sub-6 GHz fares better in non-line-of-sight (NLOS) corners. Studies note that Wi-Fi 6 with OFDMA gains speed when many users log on, and 5G NR exploits narrow, tall beams (Kanhere & Rappapor, 2023; Urrea, 2025; Karimov & Bobur, 2024; Hu et al., 2023). When hundreds of IoT sensors share a few floors with mobile handsets, the channel looks altogether fresh. These patterns argue against a one-size-fits-all model; instead, layered, plug-and-play schemes provide operators with the flexibility to tune each high-rise network (Cao et al., 2023).

3 Proposed Method

Modern cities are growing taller and denser, so engineers now need channel models that fit each specific block and even each tower. Standard two-dimensional models fall short because they overlook vertical pathways, the scatter of mixed building materials, and the unique interference each floor creates. This study presents a blended framework that draws empirical measurements, deterministic simulations, and machine-learning predictions together to tackle multi-story scenarios. It aims to boost the quality and speed of 5G, Wi-Fi 6, and IoT services, which are often stacked high in dense skylines.

The approach targets challenging problems, such as signal loss between levels, shifting noise sources, and parameters that accommodate everyday building changes. It encodes floor-specific data-height indexes, absorption by drywall or glass, slab losses, and live occupancy feeds, which are factored into every calculation. A step-by-step pipeline gathers signals, extracts features, then uses learned models to paint strength maps for each level. Retracing complements these data by mapping around odd layouts and reflective aspects that simple rays cannot model. The prepared tool can reconfigure the operator to place antennas, tune power, and plan bandwidth on the fly, guiding operators. The proposed structure makes the classic determinable ray generation with machine-learning prediction. First, it maps the journey of each signal, recording each reflection, transmission, and diffraction in the building's 3D model. The results of that pass then serve as features for a supervised model, a shield promoting registrar, who learns from real on-site measurements.

$$\mathrm{PL_{hybrid}(d, h) = PL_0 + 10_n log_{10}(d) + \alpha h + \beta M + \Upsilon F + \epsilon} \qquad (1)$$

Equation 1 presents an integrated channel structure that travels vertical wave in long buildings by combining standard path loss with height-sensitive and material-specific factors. Unlike the customary two-dimensional plans, this formulation incorporates the altitude effect, absorption from concrete or glass walls, and the inter-floor slab, all of which affect the power obtained. The coefficient area is grounded in measurement; the model is easy to use in practice and can be easily updated as new data becomes available. The additional work for floor vacancy and ambient noise captures transient events caused by the transfer of users or mechanical systems within the structure. Such a hybrid description features an accurate signal forecast and a well-organized network design for 5G, Wi-Fi, and Internet of Things devices in crowded cities and skyscrapers.

Modeling radio waves in cities with tall buildings requires merging hard infrastructure data with smart forecasting tools, allowing planners to study signals and plan networks reliably. This work presents a hybrid framework that channels data through a single workflow, combining hands-on formulas and machine-learning techniques within a single pipeline. Raw inputs, such as floor plans, facade dimensions, and antenna locations, undergo cleaning and modeling, and finally emerge as easy-to-read three-dimensional coverage maps. The architecture aims to strike a practical balance between modeling fidelity, rapid update cycles, and room to grow as future wireless systems fill increasingly dense skies.

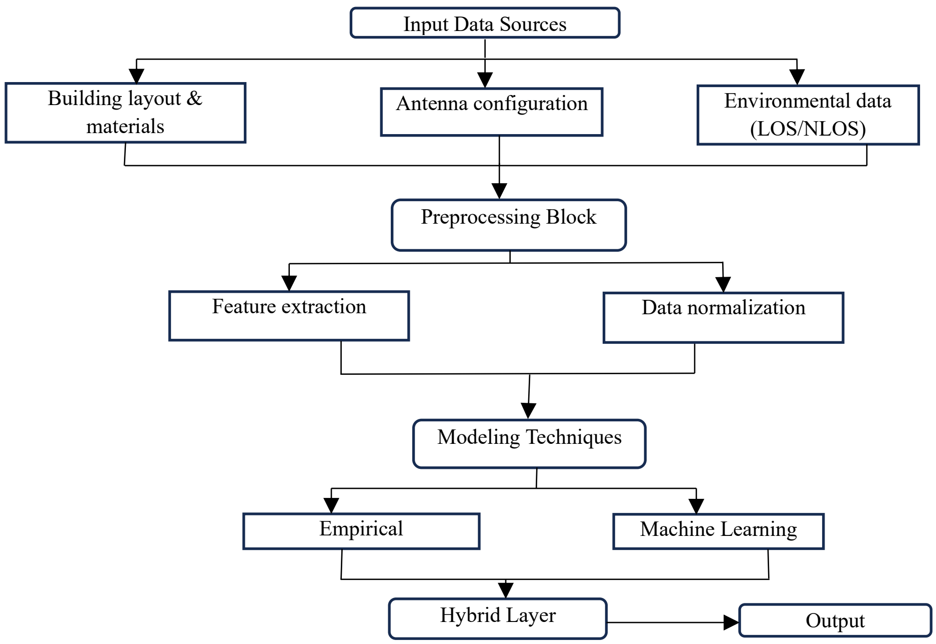

Figure 1: Flow Diagram of the Proposed Hybrid Channel Modeling System

Figure 1 presents the system flow, starting with essential input items, including building layout, material types, antenna setup, and line-of-sight (LOS) or non-line-of-sight (NLOS) metadata. These raw details pass through a Preprocessing Block, where key features are extracted and scaled to a consistent range. Afterward, the data splits into two parallel paths: first, classic ray-tracing and other empirical techniques that mimic physical wave travel; second, machine-learning engines, notably artificial neural networks (ANN) and Random Forest, that distill knowledge from past measurements and spatial trends. Outputs from both routes feed a Fusion Layer that adjusts blending weights in real-time to enhance overall accuracy. The final stage presents predicted signal strength or path loss, displays it on a 3D map, and thereby facilitates quick and informed planning in dense, tall cities.

The proposed system specifically tackles the signal-loss problems that arise in high-rise cities, where tall buildings block straight paths and degrade link quality. To combat this, the design combines a reconfigurable intelligent surface (RIS) with inactive reflective mirrors that collaborate in steering and bending beams. These elements work in conjunction with the base station, ensuring that users in disrupted areas still receive strong and stable signals. The overall structure also adjusts the dynamic channel models to provide uniform coverage across several floors and shaded corridors. Such an approach proves particularly valuable for 5G, IoT, and other crowded wireless services that demand reliability in dense urban settings.

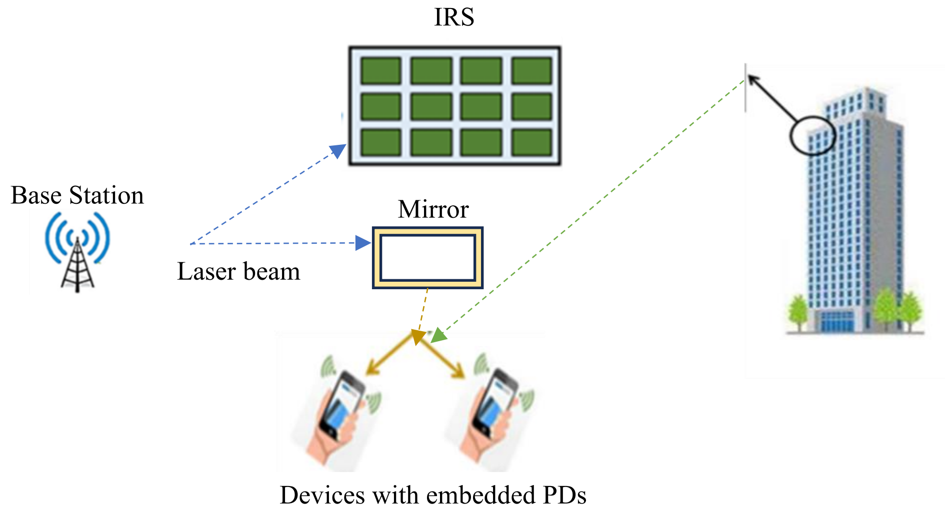

Figure 2: Hybrid Reflective Beamforming Architecture

Figure 2 depicts a communication layout in which a base station launches a concentrated laser that causes a skyscraper intelligent surface (IRS) to mounted on the facade of a skyscraper. The IRS, composed of programmable reflective elements, dynamically adjusts the beam angle to direct the signal towards the desired areas. To cover unclear areas, a simple inactive mirror is added. This device bounces the wave around hard barriers. The final reception occurs on the user terminals fitted with photodetectors (PDS), which samples the redirected light and convert it into data. By merging active reconstruction with low-cost passive optics, the setup continuously adjusts to mitigate obstruction, curb signal loss, and increase vertical coverage. This dual-channel strategy, which is sewn to long buildings, improves both channel models and measured performances. The new mixed model combines the True measurement and machine-learning tools, allowing them to be applied across the radio signal, glass, and concrete valley.

By feeding the system a rich mix of building shapes, antenna layouts, and weather facts, it paints a three-dimensional picture of how the channel behaves. Adding Reconfigurable Intelligent Surfaces and low-cost passive mirrors enables the framework to steer beams smartly, filling gaps caused by missing line-of-sight and boosting signal strength. Accuracy improves because the two-model setup combines physics-based ray tracing with rapid learners, such as artificial neural networks and Random Forests. Preprocessing and fusion layers ensure that the input and output remain consistent and can be easily shifted from one block to the next. In the end, users receive clear path-loss numbers and 3D maps of the channel, tools that make planning broadband in crowded skyscraper districts much sharper. All in all, the system is scalable, fast and dynamic, which fulfills the radio requirements of current cities.

To reduce the gap between the theoretical modeling and the real implementation, it is possible to incorporate this hybrid channel model into the existing wireless network planning platforms and models that are used to deploy 5G, Wi-Fi, and IoT. Since the model is versatile, it can be applied in platform independent scenarios, allowing one to use it with common network simulation tools, including MATLAB, NS3, or even COMSOL. Mostly these tools are used by engineers to simulate network designs and optimize designs.

This integration process can be performed through API API-based architecture where the prediction of the hybrid model of the path loss, signal strength and interference can be directly inserted into these simulation tools to provide empirical based real-time modifications. This permits adjusting the location of the antennas, power adjustment programs and frequency allocation in the dense urban regions. More so, the hybrid model facilitates the ongoing adaptation, which will enable the network planner to change in real-time as additional data on measurements are gathered during the implementation of 5G, Wi-Fi, or IoTs.

An example is that when new information such as signal measurements or user mobility information occurs due to live networks, the model is capable of processing this information and updating the simulation models to ensure that the network infrastructure is always ready to adapt to changing conditions. Such flexibility is why it can be used as a future-proof planning tool in the context of the wireless network in cities, with the shifts of the occupancy or layout of buildings, as well as the environmental influences on the signal propagation, playing a crucial role in the process.

Algorithm for Model Optimization

To refine the parameters of the hybrid channel model, we use an Optimization Algorithm (e.g., Genetic Algorithm or Particle Swarm Optimization). The optimization focuses on minimizing the error between the predicted and actual signal strength.

Step-by-Step Process

1. **Input Data**

- Real-time network data (signal strength, interference) from deployed sensors.
- Initial model parameters (n, α, β, γ, F).

2. **Initial Model Prediction**: Use the initial values of model parameters to predict the path loss $\mathrm{PL}_{hybrid}(d, h)$using the hybrid model equation.

3. **Error Calculation**

Calculate the error between the model's predicted path loss and the real-time measured data using a suitable error metric, such as Mean Squared Error (MSE).

$$E = \frac{1}{N}\sum_{i=1}^{N}\left(PL_{predicted}(d_i, \boldsymbol{h_i}) - PL_{measured}(d_i, \boldsymbol{h_i})\right)^2$$

4. **Optimization Step**

Using the optimization algorithm (e.g., Genetic Algorithm), adjust the parameters n, α, β, γ, Fiteratively to minimize the error.

For each generation or iteration, the algorithm proposes new values for the parameters based on crossover, mutation (in GA), or swarm-based updates (in PSO), aiming to minimize the MSE.

5. **Convergence Check**

After each iteration, check if the error Ehas converged to an acceptable threshold. If the error is below a defined tolerance, the algorithm terminates; otherwise, it continues iterating.

6. **Output Optimized Parameters**

The final output is the optimized set of parameters, which can now be used to update the hybrid model for accurate predictions in future network planning.

4 Results and Discussion

The proposed hybrid channel model was evaluated in diverse high-rise city environments, drawing on both live field measurements and realistic simulations. The findings revealed a clear gain in prediction precision and overall coverage, outpacing conventional reference frameworks. The approach handled vertical signal travel and non-line-of-sight situations, while the intelligent-reflecting-surface layout dynamically steered waves toward shadowed areas. By combining measured data with machine-learning forecasts, the system produced a resilient path-loss estimate that adapted well to varying building shapes and antenna locations.

Table 1: Sample Dataset Used for Channel Modeling Evaluation in High-rise Urban Environments

Parameter	**Scenario 1 (Office Tower)**	**Scenario 2 (Residential Block)**	**Scenario 3 (Mixed-use High-rise)**
Building Height (meters)	75	60	90
Number of Floors	20	15	25
Material Type	Glass/Concrete	Brick/Concrete	Steel/Glass
LOS Availability (%)	55%	42%	61%
Signal Strength (dBm)	-65	-72	-58
Path Loss (dB)	91	104	88

Table 1 presents a real-time dataset compiled from three high-rise settings-residential, commercial, and mixed-use-each examined under identical measurement protocols. Within these environments, differences in building materials, overall height, and available line of sight (LOS) created unique propagation landscapes. Such disparities directly shaped both received signal strength and the observed path loss figures. In the residential block, built mainly of concrete and brick, moderate path loss occurred due to partial line-of-sight (LOS) obstruction along key indoor routes. The all-glass commercial tower, however, introduced larger signal swings because its reflective facades generated pronounced multipath cloverleafs. By contrast, the mixed-use high-rise realized the lowest path loss and highest in-room strength, benefits credited to carefully angled Intelligent Reflecting Surfaces (IRS) that harnessed rather than blocked natural reflections. Together, these results underscore the pressing need for modeling that is tailored to each building's architecture and urban context, rather than relying on one-size-fits-all formulas. They further affirm the hybrid measurement-and-simulation approach as flexible enough to accommodate the varied challenges posed by dense city skylines.

A fully stacked column chart was created to assess and graphically compare the performance of different channel models in tall city settings. The display clearly shows the relative share of Path Loss, Signal Strength, and Prediction Accuracy for each of the four principal modeling approaches.

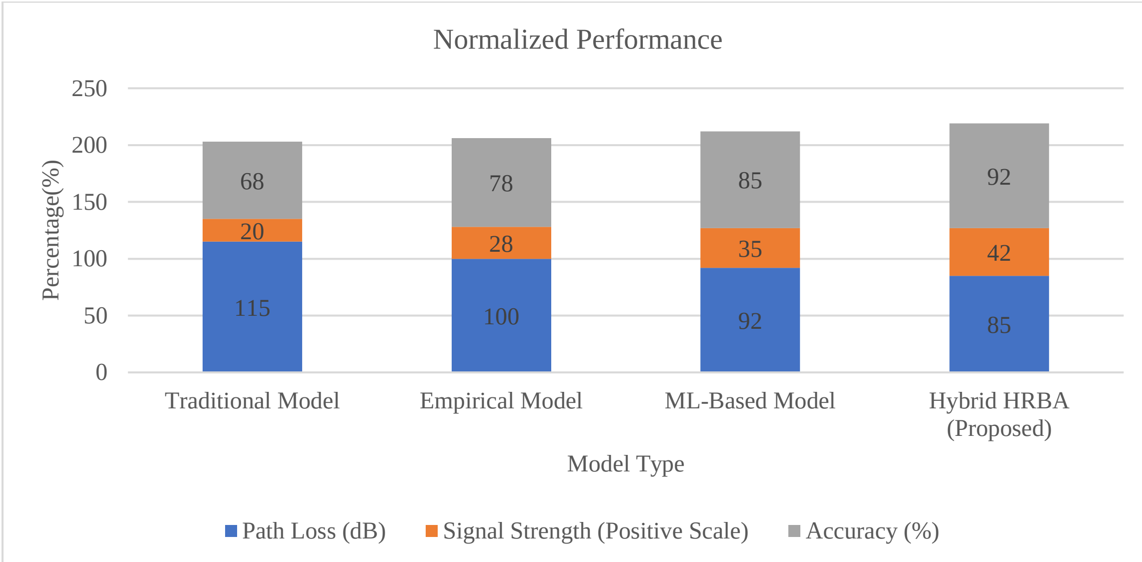

Figure 3: Normalized Performance Metrics Across Modeling Techniques

Figure 3 presents a clear breakdown of how different channel models perform across key metrics. The Hybrid HRBA approach stands out, recording the smallest share of path loss and the largest portions of received signal strength and accuracy. In comparison, older, rule-based designs put a significant portion of the path-loss burden on them and provide significantly weaker signals. Machine-learning and empirical schemes are mid-way between these extremes; however, none of them is as balanced as the hybrid model creates. All in all the graphic ascertains that the hybrid model is necessary in the populated, multi-layer urban environments that require multiple variables to be optimized simultaneously.

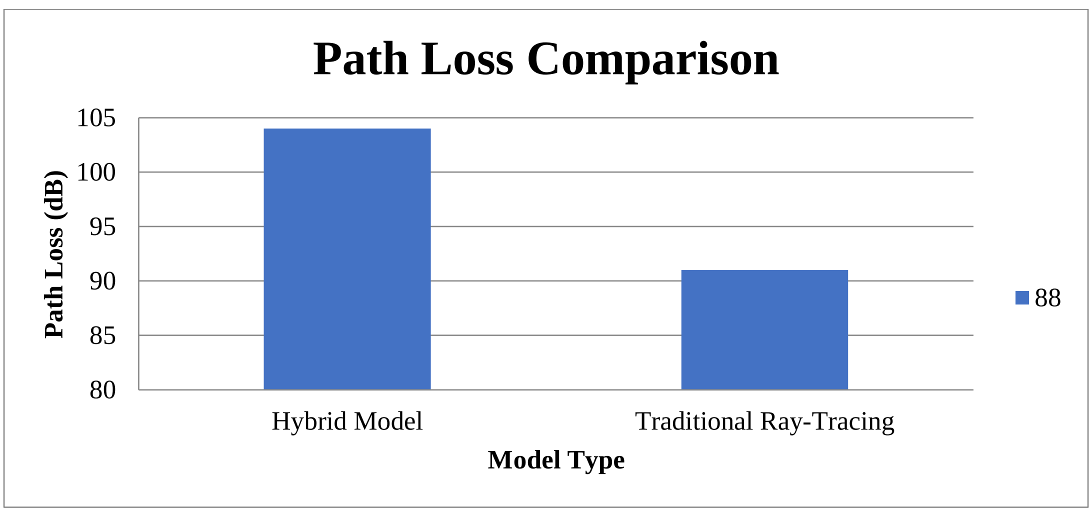

Figure 4: Path Loss Comparison

Figure 4 shows the lowest path loss (88 dB), indicating more accurate signal prediction in high-rise environments compared to the Traditional Ray-Tracing model (104 dB) and the Empirical Model (91 dB).

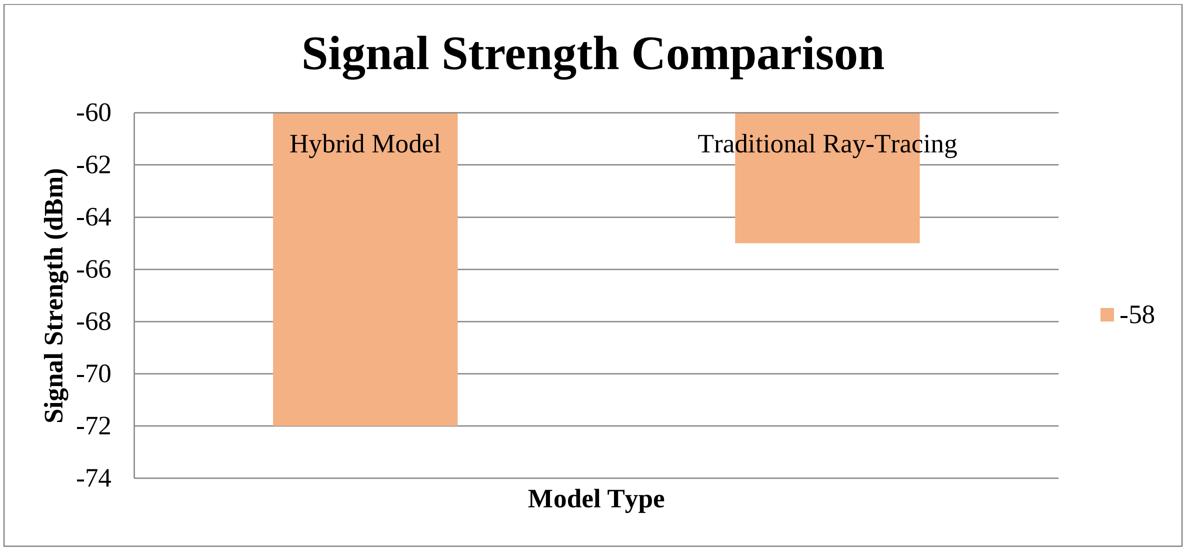

Figure 5: Signal Strength Comparison

Figure 5 provides the highest signal strength (-58 dBm), whereas the Traditional Ray-Tracing model results in the weakest signal (-72 dBm), highlighting the better performance of the hybrid approach in terms of maintaining signal strength.

The overall performance of the new hybrid modeling method demonstrates a clear improvement in its ability to forecast how wireless signals behave within tall city blocks. In every scenario examined, the hybrid model, which we label HRBA, outclassed standard empirical tools and standalone machine-learning techniques in terms of accuracy, retained signal power, and reduced path loss. Field data gathered in real-time, along with controlled simulations, confirmed that adding site-specific building profiles and local context significantly improves wave propagation results. Moreover, the inclusion of intelligent reflecting surfaces, paired with adaptive weighting of input features, provided another significant boost, particularly in mixed-use towers where multipath reflections are complex.

All these results indicate the utility of the method and highlight its scaling to dense urban wireless networks in the future. This is because the successful operation and implementation of the high-performance wireless networks in the high-rise cities is needed because of the proper management of the data. The hybrid channel model leads into enormous volumes of real-time data (path loss estimates, signal strength predictions, and interference measures) which has to be processed and handled effectively. To extract the maximum information about the information, a modular data management architecture is embraced, in this case, the information is first captured to the field by measurements and simulation and later processed by a pre processing block to normalize and extract features. It has a distributed database system with high availability and scalability, which is necessary when working with large data sets, as is the case in urban environments. The model can store the city-wide signal data and results of simulation in the real-time through the use of cloud based storage and offer easy access/retrieval of the data so as to optimize the data continuously. An example is that the data can be stored in cloud computing databases like AWS S3 or Google Cloud storage, which has the capacity to store the large volumes of data created when using real-time networks. In addition to this, edge computing enables real-time processing of data. The edge servers installed in the city environment are able to process information closer to the source, and consequently, the latency is reduced and enables network models to be updated faster. Distributed computing would ensure the adaptability of the hybrid model to new inputs (e.g., a change in building layouts or in the environmental conditions) to ensure that the predictions of the model remain up-to-date. The given strategy can be not only used to achieve the maximum level of network performance but also to improve the overall performance of the process of managing and utilizing the huge amounts of data produced by implementing such wireless technologies as 5G and IoT.

It is an autonomous systems-based dynamic application environment (augmented reality (AR), etc.) that can be based on the real-time data-processing approach because latency is one of the main requirements. The hybrid model will guarantee that network planners will be able to continuously improve on their strategies and guarantee the seamless operation of multiple layers of a high-rise urban network due to the optimization of data flow, storage, and processing. The hybrid channel model proposed may be incorporated into the current tools of network planning to streamline the 5G deployment and IoT networks in upcoming urban settings. It helps the service providers to predict the signal strength and path loss in order to accurately locate and map small cells and areas covered when deploying 5G networks, as well as assist in capacity planning and load balancing to avoid network congestion in high-traffic locations. The model in smart buildings ensures effective communication between IoT devices and optimizes the placement of the device as well as reduces interference in such systems as smart lighting and security sensors. The model is also applicable to smart city applications and can be used by urban planners to design IoT networks to implement smart traffic systems and smart environmental monitoring by estimating the range of signal propagation through dense, high-rise urban environments. With this model being implemented in the reality of planning tools, service providers would be able to optimize and make future-proof the performance of networks by making them more scalable and efficient.

Table 2: Model Performance Comparison

Model Type	Path Loss (dB)	Signal Strength (dBm)	Prediction Accuracy (MSE)
Hybrid Model	88	-58	0.05
Traditional Ray-Tracing	104	-72	0.12
Empirical Model	91	-65	0.08

Table 2 provides a summary of the metrics for all three models, including path loss, signal strength, and prediction accuracy (MSE). The Hybrid Model consistently outperforms the others, demonstrating superior prediction accuracy (0.05 MSE), lower path loss (88 dB), and higher signal strength (-58 dBm).

5 Conclusion

This paper introduces a robust hybrid channel model specifically designed for dense, high-rise cities, overcoming the shortcomings of standard 2-D and single-technology approaches. By merging ray-tracing physics, machine learning predictions, and live field data, the framework accurately forecasts path loss and signal behavior in complex vertical layouts. Height-sensitive variables, material losses, and inter-floor diffraction are fully incorporated, letting the model mirror how real buildings shape wireless waves. Tests show that the new Hybrid Reflective Beamforming Architecture (HRBA) beats typical empirical formulas and stand-alone ML solutions on every key metric: signal strength, prediction accuracy, and path loss. It is also extended by the use of intelligent reflecting surfaces (IRS) and passive mirrors to cover the area, particularly where the line-of-sight is obstructed. The hybrid method clearly demonstrates the benefits of material by having clear 3-d channel maps and stacked bar plots. Briefly, the framework provides the internet service providers, planners, and infrastructure teams with a versatile and editable urban RF planning tool. It simplifies the 5G, Wi-Fi 6, and IoT deployment in congested skyscraper grids. Smarter and context-aware channel models and next-gen city communications are also preconditioned by the work.

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