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# Optimizing Wireless Networks Performance Through Adaptive Machine Learning Strategies



**Abstract:** This research aims to enhance wireless network performance through the development and implementation of a novel machine learning-based algorithm. The methodology involves comprehensive data collection in the Uttarakhand region, specifically in Dehradun, Haridwar, and Rishikesh, through LTE network drive tests. The collected data, over six months, serves as the foundation for the proposed algorithm. The research design focuses on parameterizing essential factors of path loss to optimize coverage. Various drive test tools, including NEMO, Agilent, TEMS, and XCAL-Mobile, are employed to measure and analyze field Received Signal Strength Indicators (RSSI) data. Statistical tools are utilized to collect network parameters, assess coverage, and analyze real-time mobile network data. The research objectives include the development and evaluation of the machine learning algorithm, comparing its performance across diverse network scenarios, and benchmarking against existing state-of-the-art algorithms. The proposed methodology provides a structured and relevant framework to achieve these objectives, fostering advancements in wireless network optimization through innovative machine-learning approaches.

**Keywords:** Improving, Wireless, Network, Performance Using, Machine Learning, Received Signal Strength Indicators, artificial intelligence, Close-In, Floating-Intercept.

## I. INTRODUCTION

The last decade is marked by an exponential increase in the demand for data over the Internet, from several devices, machines, mobiles, and smart power grids, generating a need for ubiquitous wireless networks for broader coverage and robustness. The next-generation technological revolution will provide us with exceptional abilities and insights into the future standards to achieve unprecedented fast, efficient, and powerful communication networks. For developing a high-quality cost-effective wireless communication system dependency on experimentation and evaluation becomes crucial. To satisfy the emerging needs of the users of high data capacity and optimal quality, network planning has to be done precisely considering the topological design, environmental conditions, and vegetation of the area under investigation. Propagation modeling is used to define and develop a propagation model that encompasses the coverage of an area and can also be tailored to make for the coverage holes. Radio propagation losses are subjected to multivariate factors like reflection, deflection, and scattering due to buildings, vegetation, hills, etc. Empirical propagation models are predominantly univariate and consider only one factor at a time.

Therefore, the prediction provided by these models is not accurate. Machine learning-based models can consider multivariate factors altogether due to their learning and knowledge representation capability to predict propagation losses, providing accurate and efficient prediction.

### A. WIRELESS NETWORK

Communication accomplished without any wired connection between the devices is wireless communication. Electromagnetic waves are used as the medium of transmission and an electromagnetic spectrum is divided into

well-defined channels that are used for communication. There are several advantages of using a wireless network for communication over a wired network. Firstly, user's convenience and flexibility have improved due to the mobility attained in using the devices. This has also enriched productivity by incorporating more collaborated work effortlessly. Secondly, deployment cost, time, and effort have been reduced remarkably because of minor installation

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and setup requirements for wireless communication networks. Thirdly, the network can be easily scaled and altered according to the demand. Thus, wireless networks emerge out to be quite beneficial and cost-effective. Along with having several advantages, there are certain limitations of the wireless communication network. Firstly, the mobility of the user is hampered when it moves away from the

range of the transmitter affecting its performance. Secondly, electromagnetic waves are prone to interference problems that may distort the signal carrying information. Thirdly, a wireless communication network is vulnerable to security threats where critical information can be hacked by unauthorized persons.

#### A. MACHINE LEARNING

The next-generation ever-evolving wireless network is expected to reinforce the radical requirements of high reliability, ultra-low-latency, and availability in real-world applications as well as services. New standards in the technology are required to ensure high QoS to the users. Integrating Machine Learning (ML) with advanced wireless networks seems to be the potential solution to the current challenges of next-generation wireless networks. Machine Learning was evolved in the year 1950 and it will transform the world with the upcoming 5G technology.

Machine Learning is an approach that supports a system to learn and discern similar patterns from the hitherto unexplored data without being programmed. A ML approach is built depending upon the set of features fed to it as input training data. The developed model is used for predictions over the new set of data provided. There are various machine learning algorithms available that are trained according to the given data obtained from the real-world scenario to develop a model. These algorithms correlate the relationship between the input features present in the training data and corresponding output variables provided to estimate prediction.

Machine learning (ML) is a subset of artificial intelligence (AI) that focuses on the development of algorithms and models that enable computers to learn from data and make predictions or decisions without being explicitly programmed for a task. The core idea behind machine learning is to create systems that can automatically learn and improve from experience.

In the realm of machine learning, the training process is fundamental to the development of models capable of making accurate predictions or decisions. This training is conducted on expansive datasets comprising input features, which represent the characteristics or attributes of the data, and

corresponding output labels or target values. The model learns from this paired information, discerning patterns and relationships between inputs and desired outputs. Following the training phase, the model's proficiency is assessed using a distinct set of data known as testing data. This separate dataset allows for the evaluation of the model's ability to generalize its learned patterns to new, previously unseen examples. The testing phase is crucial in gauging the model's performance and ensuring its effectiveness in real-world scenarios beyond the specific instances encountered during training. This division between training and testing data is vital for validating the model's generalization capabilities and enhancing its reliability in making predictions or classifications in diverse and dynamic environments,

#### LITERATURE REVIEW

**Salous, et al. (2020) [1]** investigated the frequency range of 0.8 GHz to 73 GHz for urban and suburban environments by carrying measurements. A channel model for a future 5G wireless network was tried by conducting field measurements and data analysis with environmental parameters considering LOS and NLOS conditions.

**Hasan, et al. (2020) [2]** identified the most appropriate path loss model for Erbil city, Iraq. Field measurements have been carried out to collect data at 1800 MHz for urban and suburban environments. COST 231 models were suitable for network planning and designing in Iraq.

**Tataria, et al. (2021) [3]** presented an evolution and standardization scheme for the first to the fifth generation of path loss models by covering operating frequency range between 800 MHz to 100 GHz. It also considered the fading effects in propagation. Enhancement of deterministic modeling has been done for all generations along with extensive modeling techniques which were required for simulating mm Wave channels.

**Wen, et al. (2019) [4]** explored the reliability and stability of in-cabin communication using machine learning methods which are utilized for predicting path loss for varying regions at a particular frequency.

**Nadir, et al. (2018) [5]** analyzed propagation models for the frequencies utilized by the 4G LTE network. The data collected from the drive test was used to obtain measured path loss and compared for the path loss incurred from the propagation models. A generalized equation of path loss models for a specific area is then generated using RMSE value by applying a neural network for forecasting.

**Ahmadien, et al. (2020) [6]** proposed a technique for predicting path loss through satellite images which were processed using deep convolution neural networks. Its performance is better as compared to the ray-tracing technique, where a 3D model of the specific area needs to be modeled. It also provides a better prediction for variable frequencies and heights of the transmitting antenna.

**Y. Zhang, et al. (2019) [7]** proposed the need to predict the path loss using optimization methods that are more accurate and less complex to fulfill the rising demand of fifth-generation mobile networks. The artificial neural network was revealed to be a better approach as compared to the log-distance model approach. As enormous data is required by the machine learning approach, to provide reliable outcomes, data expansion has been carried out by reusing the old data for a new scenario, or classical models are utilized to generate data samples for training the machine learning models.

## RESEARCH METHODOLOGY

The most important and primary step for carrying wireless network optimization is data collection. It involves data collection, measurement, and analysis to observe significant insights for research with the support of verified technical methodology. To obtain valuable data-driven conclusions, authentic and information-enriched data collection is critically required for statistical investigation.

### A. RESEARCH DESIGN

An investigation is required to parameterize the essential factors of path loss so that coverage in the area can be improved accordingly. Empirical models are available to evaluate the network performance but these models suffer in their performance when applied in an area that is different from the medium of their

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An investigation is required to parameterize the essential factors of path loss so that coverage in the area can be improved accordingly. Empirical models are available to evaluate the network performance but these models suffer in their performance when applied in an area that is different from the medium of their

development. Before their utilization, they need to be tuned according to the desired medium. Repeating the same exercise every time for every new location is time-consuming, costly, and requires complex computation which is not feasible. Researchers are slowly grabbing the efficiency of the machine learning approach that can develop a path loss model with great ease and accuracy. This research activity needs the support of exhaustive field data to critically analyze the underlying determinants, which can have mutual behavior. Therefore, data collection becomes a prime and fundamental prerequisite for the domain of network planning and channel modeling.

### A. DATA COLLECTION

The region of Uttarakhand has been identified for investigation where the test has been performed over the LTE network and the drive test path is decided. The drive test has been carried out at Dehradun, Haridwar, and Rishikesh as the drive test starts data is collected through the handset equipped with the data collection XCAL software that is attached to a laptop and kept in a vehicle. 90,000 samples were collected at a moderate speed of 20 Km/h for six months. The generated log files of the samples were collected and saved for testing. These log files are then analyzed using analysis tools available for data analysis and interpretation.

### B. WIRELESS NETWORK PLANNING AND OPTIMIZATION

The radio network consists of the mobile station and base trans-receiver station as the fundamental component. The coverage area around the BTS is divided into 3 sectors which consist of cells.

### C. WIRELESS NETWORK OPTIMIZATION

Optimization includes supervising, validating, and developing the performance of the wireless network.

### D. RECEIVER SENSITIVITY

The performance of radio, when it is not subjected to external interference is governed by its sensitivity. This is the required input level to achieve a given degree of performance. This description is important as it identifies that there is no such thing as a single sensitivity, but rather that there will be different values for different degrees of performance. In some cases, it

will be necessary to determine sensitivity from graphs of bit error rate (BER), but in most practical cases, commercial equipment has been used. For digital equipment, the sensitivity used must be that for the conditions prevalent at the antenna, particularly whether it is moving or not.

### C. DRIVE TEST TOOLS FOR MEASUREMENT

Following software and hardware drive test tools are available to collect and analyze field RSSI data

- NEMO

NEMO is a tool that assists in drive tests for evaluating and tracking the radio wireless network and interface with outdoor and indoor calculation with different alternatives like data videos, voice & quality.

- AGILENT

Agilent's data test platform or GPRS presents a true drive test solution.

- TEMS

TEMS offers solutions to problems associated with wireless network optimization. Regardless of network technology, the TEMS optimization solutions product family helps during every stage of the network life cycle,

making the network perform at the high level expected by the subscribers. TEMS offers solutions for preparing, promoting, improving, fine-tuning, and extending mobile networks.

configurations. Drive test is done to execute two investigation cluster drive tests and single-cell function tests. To evaluate the coverage and quality of a transmitter cluster drive test is performed. Cluster drive test generally examines a group of cells through the details of the parameters attained from network data.

**D. DATA ANALYSIS**

The data analysis obtained from the collected data represents the quality of coverage which can be further optimized to deliver enhanced services more efficiently. The methodology involves Software, Hardware, Installation, Site selection.

**RESULT AND DISCUSSION**

**A. Signal Strength**

The measured signal strength clearly represents the variation of its strength dependence on separation between the receiving as well as transmitting antenna and area in which measurement is carried out. The signal measurement has been carried out in three cities of Uttarakhand namely Dehradun, Haridwar, and Rishikesh.

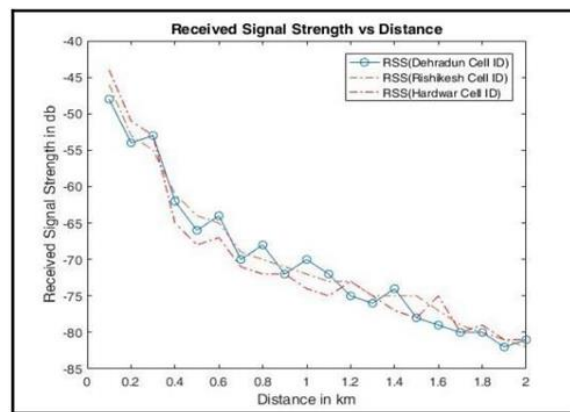


FIGURE 1: RECEIVED SIGNAL STRENGTH (DBM) WITH DISTANCE (KM)

FIGURE 1 SHOWS THE REDUCTION IN RECEIVED SIGNAL POWER AT RECEIVER WITH RESPECT TO INCREASE IN DISTANCE FROM THE TRANSMITTER OF THE MOBILE USER. IT HAS BEEN CONCLUDED THAT THIS DECREASE OF SIGNAL STRENGTH IS DUE TO THE ENVIRONMENTAL CLUTTER X CAL-MOBILE

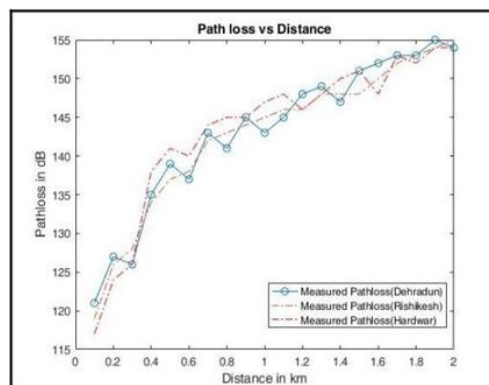


FIGURE 2: PATH LOSS (DB) VS DISTANCE (KM)

Figure 2 indicates deviation in path loss for three different cities of Uttarakhand named namely Dehradun, Haridwar, and Rishikesh. The field measured data start recording from 300m to 1900m in all three cities. The received signal strength in Dehradun, Haridwar, and Rishikesh at 300m is -53 dB,

-55 dB, and -53 dB respectively. The maximum path loss in Dehradun, Haridwar, and Rishikesh is 155 dB, 153 dB, and 151 dB respectively. The sensitivity of received power is influenced by design parameters. The signal variation at the user end is also due to the presence of obstacles in the propagation path and radiopropagation channel losses. The propagation model is assessed on the error value which is the difference between the calculated and the path loss prediction value. Lower the error value better will be the performance of the propagation model. It is expressed in decibels (dB).

**A. COMPARISON BETWEEN PREDICTED AND MEASURED FIELD DATA**

The transmitter receiver distance metric and the received signal strength metric has been recorded in meter (m) and decibels (dB) respectively in the current research work. For the analysis purpose, the field measurement has been done in three base stations in Dehradun, Rishikesh, and Haridwar of Uttarakhand, India.

**TABLE 1: AVERAGE SIGNAL STRENGTH MEASUREMENTS OF DEHRADUN**

<b>Drive Test Point</b>	<b>Distance</b>	<b>Received signal strength (dB)</b>
Test point 1	300	-53
Test point 2	500	-66
Test point 3	700	-70
Test point 4	900	-72
Test point 5	1100	-72

**Table 2: Average Signal Strength Measurements of Rishikesh**

<b>Drive Test Point</b>	<b>Distance</b>	<b>Received signal strength (dB)</b>
Test point 1	300	-55
Test point 2	500	-64
Test point 3	700	-69
Test point 4	900	-71
Test point 5	1100	-73

**TABLE 3: AVERAGE SIGNAL STRENGTH MEASUREMENTS OF HARIDWAR**

<b>Drive Test Point</b>	<b>Distance</b>	<b>Received signal strength (dB)</b>
Test point 1	300	-53
Test point 2	500	-68
Test point 3	700	-71
Test point 4	900	-72
Test point 5	1100	-75

With the help of Table 1, 2, and 3 received signal strength in three cities was compared, it was also observed that with the increase in distance received signal strength at Dehradun decreased most. The field measured data start recording from 300m to 1100m in all three cities with a distance of 200m each test point.

**A. SELECTION OF OPTIMAL FIT MODEL**

From the plotted graphs, it was observed that the all- propagation model does not predict precisely for propagation selected terrain of Uttarakhand. This is because the characteristics of topography, particularly the size and density of buildings, and climatic

wave transmission.

TABLE 4: THE ERROR IN BETWEEN PATH LOSS MODELS AND MEASURED DATA (DEHRADUN CELL ID)

**Table 5: The error in between path loss models and measured data (Rishikesh Cell ID)**

Error at Distance (d) in meters	Free Space	COST 231	ECC3	Egli	Okumura	Hata	SUI	Ericsson
300	-40.91	-11.59	0.87	-38.32	6.04	-16.64	10.84	-1.32
500	-45.47	-13.59	2.19	-38	-1.48	-18	11	-3.58

Table 6: The error in between path loss models and measured data (Haridwar Cell ID)

Error at Distance (d) in meters	FreeSpace	COST 231	ECC3	Egli	Okumura	Hata	SUI	Ericsson
300	-38.91	-9.69	2.87	-36.32	8.04	-14.64	12.84	-0.67
500	-49.41	-17.14	6.91	-42.44	-2.51	-22.25	7.92	-7.58
700	-49.55	-15.16	5.08	-39.60	-2.59	-20.10	11.55	-6.15
900	-48.36	-12.44	2.90	-36.23	-1.41	-17.38	15.13	-3.83
1100	-49	-10.00	3.	-35	2.66	-17	16.47	-4.19

It has been observed from Table 4, 5, and 6 that the ECC 33 model has the smallest error. So, the ECC 33 is the optimal propagation loss model.

### CONCLUSION

Extraordinary challenges have been constituted for the mobile communication industry due to novel breakthroughs. The unprecedented increase in wireless data traffic has been noticed as mobile communication has evolved into the usual activities of humans in their regular lives. Anyhow, the existing wireless mobile communication technologies with finite bandwidth limitations have arrived at their peak state where it is inconceivable to furnish expected data requirements. Thus, the employment of advanced wireless technology, 5G along with the allotment of the higher frequency spectrum is the appropriate solution to the connectivity issues. The use of propagation models for network planning and monitoring is an ideal approach for improving the QoS of the advanced wireless system which is highly dynamic. However, the demand for connectivity on the go with varying data rates is a challenging issue that cannot be resolved with the conventional model-based approach that can merely consider univariate parameters for optimization. The connectivity of a region depends on the multivariate parameters that depend directly or indirectly upon each other. Therefore, the machine learning-based approach is anticipated to be a practicable approach that is capable of accounting for all necessary information and parameters required for power decisions. It has been observed that the machine learning approach is highly advantageous over the conventional model-based approach in improving the signal coverage of a selected area with enhanced efficiency and performance with reduced complexity and cost.

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