J. Integr. Sci. Technol. 2024, 12(3), 758

Journal of Integrated
SCIENCE & TECHNOLOGY

Radio network TETRA path loss calculation by statistical polynomial kernel radial wavelet network models for RSSI predication and comparison in undulating area

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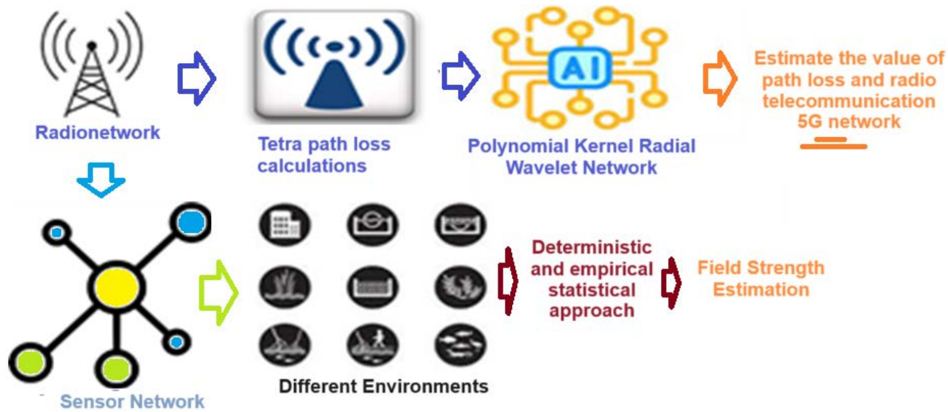
Received on: 12-Jul-2023, Accepted and Published on: 10-Nov-2023

Article

ABSTRACT



Radio Network planning is the most important part of the whole network design owing to its proximity to mobile users. However, earlier radio network approaches failed to account for the right selection of training parameters for diverse environmental circumstances in radio communications networks, resulting in poor reliability and unreliable coverage. Hence, a novel Radio Network TETRA Path Loss Calculation by statistical Polynomial Kernel Radial Wavelet Network Models for RSSI Predication and Comparison in Undulating Area has been designed for TETRA path loss calculation by deterministic, empirical RSSI Predication and effectively select the parameters in different environment. In existing techniques, the parameter selection, such as radio wave path calculation, frequency, antenna heights, distance, and angle elevation, are not analyzed accurately. Hence, a novel technique, namely Polynomial Kernel Radial Wavelet Network (PKRWN), has been designed in which the attenuation clustering radio environment to estimate the value of path loss and radio telecommunication 5G network and provide statistical descriptions of the relationship between path loss and propagation parameters. Moreover, it suffers from low stability because the Received Signal Strength Indicator (RSSI) is easily blocked and easily interfered by objects, environmental effects, and climatic conditions. Hence, a novel technique, Arid-Terrain-Ridge Integrational Radio Sensor Network, has been designed to get good stability of RSSI in various environmental effects such as urban, suburban, rural, hilly, plain, and desert areas. Also, the Deterministic and empirical statistical approaches are used to estimate the field strength. As a result, it accurately estimates the appropriate parameters in radio telecommunication networks with various environments with good stability and predictions of RSSI.

Keywords: Radio network, telecommunication, path loss, TETRA, frequency, environmental effects, Received Signal Strength Indicator (RSSI)

INTRODUCTION

A radio network is a significant component of a mobile telecommunication system that uses a radio connection to connect individual devices to other portions of a network. A radio network is a fundamental strategy for resolving the contradiction between exponential traffic growth and severe spectrum scarcity.[1,2]

The main aim of radio network planning is to provide a cost-effective solution for the radio network regarding coverage, capacity, and quality.[3] The detailed radio network plan can be subdivided into five sub-plans: link budget calculation, coverage, capacity planning, spectrum efficiency, and parameter planning.[4] The major change in the radio network planning in the TETRA network is due to the introduction of the Complex modulation scheme, Access Point (AP) terrain relation and signal fading schemes.[5] Radio signal path loss is simply the drop in power density of an electromagnetic wave as it travels through the environment. Path loss prediction models are survey techniques that estimate signal strength at various places. They aid in determining the signal strength of an area before installing equipment.

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Cite as: *J. Integr. Sci. Technol., 2024, 12(3), 758.*
URN:NBN:sciencein.jist.2024.v12.758

 ISSN: 2321-4635
http://pubs.thesciencein.org/jist

Path loss is signal blurring caused by reduced signal strength between the receiving and sending stations. Radio waves traveling through the lower atmosphere are used in wireless communication systems.[6,7] The transmission path between a transmitter and a mobile receiver varies depending on where you are, ranging from a straightforward view path to one with obstacles such as hills, trees, buildings, and other man-made structures.[8] In mobile communication, propagation loss due to reflection, refraction, diffraction, and scattering affects the electric field intensity of signals emerging from a transmitter, resulting in weak received signals and route loss due to a drop in the power density of an electromagnetic wave as it transmits from the broadcasting antenna to the receiving antenna.[9] Path loss is signal fading caused by signal power reduction between receiving and transmitting stations. Predicting path loss (PL) is critical for forecasting transmitter coverage and enhancing wireless network efficiency.[10,11] An empirical or deterministic method is used to estimate the environment-related path loss. Empirical models often comprise a set of equations generated from extensive field data, whereas site-specific deterministic models employ physical principles of radio propagation to forecast signal intensity or path loss at a given place.[12,13]

Modeling signal propagation and losses is a critical component in planning and deploying mobile communication systems.[14] The mobile system is based on electric radio connections placed inside the troposphere, the seat of many meteorological and climatic phenomena (rain, snow, fog, etc.), or above the ground with numerous obstructions (structures, vegetation, etc.) inside buildings.[15] With new wireless communication technologies and the increasing size of radio networks, network planning and resource optimization tasks are becoming more and more challenging. This is because radio resources are scarce these days due to the increasing number of subscribers and the many different types of networks operating within the limited frequency spectrum. Secondly, deploying and operating a large network is expensive and requires careful network dimensioning to ensure high resource utilization.

As a consequence, manual network design and tuning for improving radio resource allocation are most likely to fail in current and future networks. This necessitates developing algorithms, models or tools. The goal is to identify relevant problems for each path loss model and method, formalize the problems, and find reasonable solutions. The novel Radio Network TETRA Path Loss Calculation by Deterministic, Empirical, Polynomial Kernel Radial Wavelet Network Models for RSSI Predication and Comparison in Undulating Area has been designed to overcome these issues. The main contributions of this paper are as follows:

❖ In Radio Networks, a Polynomial Kernel Radial Wavelet Network has been introduced to estimate the value of path loss and radio telecommunication network and provide statistical descriptions of the relationship between path loss and propagation parameters such as frequency, antenna-separation distance, and antenna heights.

❖ In the radio telecommunication network, the Arid-Terrain-Ridge Integrational Radio Sensor Network has been introduced to get good stability of RSSI in various environmental effects such as urban, suburban, rural, hilly, plain, and desert areas. Also, the Deterministic and empirical statistical approach is used to estimate the field strength (or signal power) directly from the path profile and provide estimations of field strengths (or power) and knowledge of the terrain profile.

Literature Review

Anusha P C et al[16] presented a lightweight position detection approach that leverages the RSSI of the anchor nodes to determine distance using GPS from the sensor. This distance is calculated using a unique method in which 2D distance equations are employed to predict the relative layout of the node. The designed technique was evaluated using simulation, and the method was discovered to have an acceptable amount of inaccuracy. The methodology can calculate the position using only four detector nodes. However, still need to find any malicious activity in the wireless sensor network (WSN).

Sana Messous et al[17] proposed various localization methods are the basis of numerous wireless sensor network applications. Multi-hop localization algorithms are applied to reduce the substantial localization error in the original. The received signal strength indication (RSSI) and the polynomial approximation are used to calculate the distance between unknown nodes and anchors. Furthermore, their proposed algorithm employs a recursive calculation of the localization process to increase location estimate accuracy. However, there is a need to consider the same communication radius, the average localization error.

Nasir Faruk et al[18] collected data to develop path loss models based on artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), and Kriging techniques. Empirical propagation models are prone to introducing large forecast errors. Many heuristic algorithms and geographic approaches have been developed to minimize path loss prediction errors. This work assesses and discusses the effectiveness of empirical, heuristic, and geospatial approaches for predicting signal fading in the very high frequency (VHF) and ultra-high frequency (UHF) bands in typical metropolitan contexts. However, there is a need to consider heuristic methods which help to reduce the large prediction errors associated with empirical models.

Jawad et al[19] developed two reliable path-loss models where work based on the connection between RSSI and distance in a farm field. The path-loss models were developed using the MATLAB curve fitting tool and RSSI data gathered in a Lucerne farm field. The performance of the regression line was greatly enhanced by achieving an ideal straight-line fitting over the RSSI data using the EXP-PSO and POLY-PSO path-loss models. An accurate path-loss model was required for smart agricultural applications to assess the behaviour of propagated signals and to arrange the nodes in the WSN in such a way that data transmission occurs without extra packet loss between nodes. However, increasing the number of POLY coefficient equations increases the complexity of PSO and the execution time to identify the optimum fitness function.

Nahla Nurelmadina et al[20] aim to assess the different technologies and protocols for industrial IoT applications. A thorough evaluation was done by comparing various technologies while keeping essential parameters like frequency, data rate, power, coverage, mobility, pricing, and QoS in mind. The Low Power Wide Area Network (LPWAN) uses Information Systems and Communication by Radio Waves (Sigfox), Narrowband Internet of Things (NBIoT), and Long-Range Wide Area Network (LoRaWAN) technologies to create low-power communication for IoT sensors. A cognitive low-energy architecture is introduced to provide efficient and reliable communications in a heterogeneous IIoT. It will secure the network layer by providing clients an effective platform for renting AI and different LPWAN technology. However, a model that allows for less energy, longer-running devices, and the greatest feasible data throughput utilizing the cognitive Internet of Things must be established.

Kunal Sankhe et al[21] presented the design and performance of ORACLE, a method for finding a unique radio from a huge pool of bit-similar devices (identical hardware, protocol, physical address, MAC ID) using just IQ samples at the physical layer. ORACLE trains a convolutional neural network (CNN) that balances computational time and accuracy. However, need to improve the classification accuracy in a dynamic environment is required.

Carlos Baquero Barneto et al[22] analyzed and illustrated the potential of OFDM-waveform-based radio sensing in 5G NR base stations, focusing on millimeter Wave (mmW) use scenarios. Initially, a basic target range and velocity estimate resolution analysis for various carrier bandwidths and observation time windows is performed, demonstrating that near-to-centimeter-level ranging precision may be attained. Thereby, when performing the receiver and transmitting simultaneously, special focus is placed on analyzing and suppressing direct self-interference. Finally, actual RF measurements in the 28 GHz working band, including self-interference cancellation and radar processing solutions, are supplied and examined. The results show that direct self-interference cancellation may be performed successfully and that targets can be accurately detected and tracked. However, further need to assess and visualize the potential of the 5G NR network for sensing.

Alok Kumar et al[23] analyzed a cognitive radio (CR) sensing performance assessed in terms of false-alarm probability (Pf) and detection probability (Pd). IEEE 802.22 wireless regional area network is a common cognitive radio standard for accessing underutilized licensed TV band frequencies. According to this standard, the false-alarm probability of CR should be B 0.1, and the detection probability should be C 0.9. Moreover, the detection and false-alarm probabilities in the spectrum sensing technique are highly influenced by the threshold value used, and threshold selection is a critical step in determining the status (presence/absence) of PU. The threshold is determined by fixing one parameter (Pf or Pd) while optimizing the other (Pd or Pf). Moreover, despite attaining one of the intended sensing parameters at low SNR, the other sensing parameter suffers significantly. However, the multiband spectrum sensing method must be considered when PU changes its condition throughout the sensing time.

Amjad Ali et al[24] presented a strategy for lowering the SU channel switching rate and increasing channel selection adaptability. Moreover, making channel-switching judgments based on crisp logic is not an appropriate technique in brain-empowered CR networks (CRNs), as sensing input is imprecise and erroneous and entails a significant amount of uncertainty. To improve the overall throughput of CRNs, this paper presented a fuzzy logic-based decision support system (FLB-DSS) that deals with channel selection and switching. However, if the SU switches channels repeatedly, its performance suffers greatly.

From the analysis, it is clear that Anusha et.al.[16] design need to find out any malicious activity in WSN,[17] need to consider the same communication radius as the average localization error,[18] need to consider heuristic methods which help to reduce the large prediction errors associated with empirical models,[19] it increases the computation time, [20] need to establish a model that allows for less energy, longer-running devices, and the greatest feasible data throughput utilizing the cognitive Internet of Things,[21] need to improve the classification accuracy in a dynamic environment,[22] further need to assess and visualize the potential of the 5G NR network for sensing,[23] need to consider multiband spectrum sensing method when PU changes its condition throughout the sensing time,[24] if the SU switches channels repeatedly, its performance suffers greatly.

Radio Network Tetra Path Loss Calculation By Deterministic, Empirical, Polynomial Kernel Radial Wavelet Network Models For Rssi Predication And Comparison In Undulating Area

Path loss (PL) is a critical statistic in communication systems because it shows a radio wave's decrease in power density as it travels through the channel. Previous methods did not consider the appropriate selection of training parameters in radio communications networks with distinct types of environments. Hence, a novel Radio Network TETRA Path loss calculation by deterministic, empirical, AI models for RSSI prediction and comparison in an undulating area has been designed for TETRA path loss calculation by deterministic, empirical also RSSI Predication and Comparison in Undulating Area effectively select the parameters in different environments. Existing methodologies did not correctly analyze parameter choices such as radio wave path computation, frequencies, antenna heights, distance, and angle elevation. Hence, a novel technique, namely Polynomial Kernel Radial Wavelet Network, has been designed in which the attenuation clustering radio environment is utilized to estimate the value of path loss and radio telecommunication 5G network and provide statistical descriptions of the relationship between path loss and propagation parameters such as frequency, antenna-separation distance, antenna heights.

Moreover, it has poor stability only because the Received Signal Strength Indicator (RSSI) is easily blocked and interfered with by objects, environmental factors, and weather conditions. Hence, a novel technique, Arid-Terrain-Ridge Integrational Radio Sensor Network, has been designed to get good stability of RSSI in various environmental effects such as urban, suburban, rural, hilly, plain, and desert areas. Also, the Deterministic and Empirical statistical approach to analyze the propagation of radio waves in the environment considers the mechanisms described above and is used to estimate the field strength (or signal power) directly from the path profile (profile of the terrain between the transmitter and the receiver). These methods adjust the terrain elevation to take account of the earth's curvature and are intended to provide estimations of field strengths (or power) and knowledge of the terrain profile.

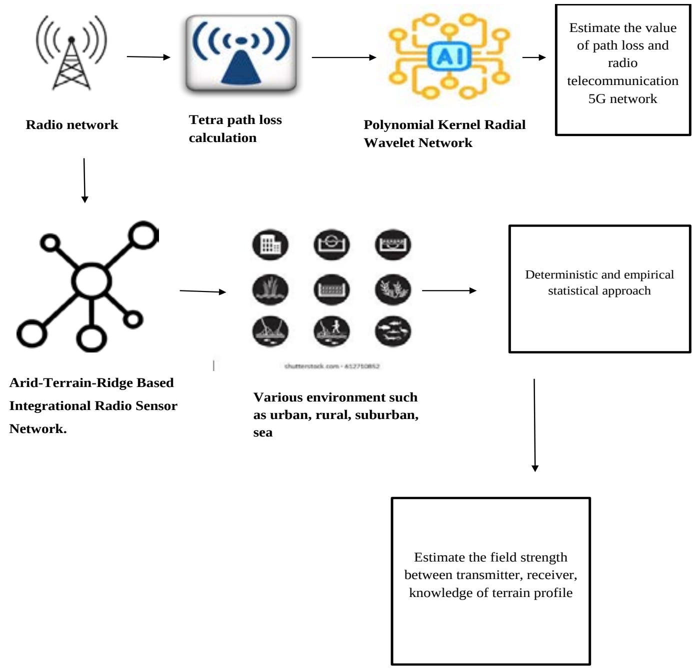

Figure 1: Architectural diagram of the designed model

Figure 1 represents the architecture diagram of the radio network tetra path loss calculation by deterministic, empirical, polynomial kernel radial wavelet network models for RSSI prediction and comparison in undulating areas. Here, the AI model named a polynomial kernel radial wavelet network in which the attenuation clustering radio environment estimates the tetra path loss calculation and analyse the radio telecommunicating 5G network, arid-terrain-ridge based integrational radio sensor network in which the deterministic and empirical statistical approach get good stability of RSSI in various environmental effects such as urban, suburban, rural, hilly, plain, desert area analyze the propagation of radio waves in the environment.

These models were developed from data obtained from extensive measurements in different environments. These models use simple equations with little dependence on the cartographic data and are only valid for short ranges of frequencies and specific environments (urban, suburban, open/rural, sea, etc.). There are two types of input features: system-dependent parameters and environment-dependent parameters. System-dependent parameters are independent of the propagation environment, such as carrier frequency, transmitter and receiver heights and location. Other system-dependent properties, such as the antenna separation distance and the angle between the line-of-sight path and the horizontal plane, may be obtained using the parameters above. The physical environment and weather patterns influence environment-dependent parameters. Terrain, building conditions, and vegetation conditions are examples of geographical environment parameters. Most are available through three-dimensional (3D) digital maps, topographic databases, and land cover databases. Temperature, humidity, and precipitation rate are among the weather parameters.

Polynomial Kernel Radial Wavelet Network

Polynomial Kernel Radial Wavelet Network is utilized to select the appropriate parameters, compute the parameters such as radio wave path, frequency, antenna heights, distance, and angle elevation, and estimate the value of path loss. It is deployed to the network edge. To address individual devices' limiting computation, storage, and power, 5G design should explore exploiting scattered computing capabilities across network edges and end-devices via multiple access edge computing.

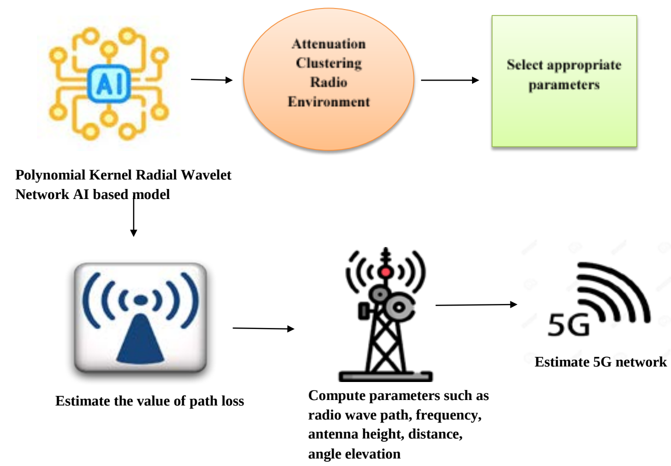

Figure 2: Architecture diagram of Polynomial Kernel Radial Wavelet Network

Figure 2 represents the polynomial kernel radial wavelet network AI-based model in which the attenuation clustering radio environment accurately selects the appropriate parameters estimate the value of pathloss and compute the parameters such as radio wave path, frequency, antenna height, distance, angle elevation and estimate 5G network.

Here, Polynomial Kernel Radial Wavelet Network is introduced for the selection of appropriate parameters and to estimate the value of path loss and radio telecommunication 5G network.

$$k_{polynomial}(a_m, a_n) = (a_m . a_n + x)^y \tag{1}$$

In equation (1), where $k_{polynomial}$ is the polynomial kernel characterizes the relationship between the training data in the feature space and the polynomials of the frequencies, x is to calculate the distance and y is to calculate height of the antenna, m and n is the angle elevation.

$$a(g) = \frac{1}{L}\sum_{e=1}^{L} \hat{a}_i\,(g) \tag{2}$$

In equation (2) $a(g)$ denotes the predicted path loss value at the radial network, L is the total number of parameters selected. Radio waves are used to transport data across space. At the transmitting end, some transducer converts the information to be transferred into a time-varying electrical signal known as the modulation signal; thus, the relationship is extracted. They provide statistical descriptions of the relationship between path loss and propagation parameters such as frequency, antenna-separation distance, and antenna heights. In 5G communication applications, it quickly collected a substantial volume of measured data at these new frequencies and was time-consuming and expensive.

$$a_r(f) = \sum_{i=0}^{R-1} p_i[r] q^{e^{(2i\sigma/F)^f}} \quad (3)$$

Equation 3 determines the wavelet network, where $a_r(f)$ is the summation of the number of complex-valued sinusoids K, f period in the continuous-time domain, R denotes the discrete-time index, The data symbol is $p_i[r]$. Intelligent services in 5G are expected to extend from data centres to edge networks and consumer devices. Applications operating on network edges predict user behaviour and environmental conditions, acting as perspective assistants to centralized AI based control systems. Meanwhile, federated learning may be used to train data locally and learn the global model by sharing learning models from dispersed devices to address data privacy and security concerns about distributed training on edge devices.

Then need to estimate and predict RSSI relation with Path loss it is used to receive signal strength power is described in Equation (4).

$$RSSI = -10nlog10d + A \quad (4)$$

Where n is the path loss exponent calculated using the polynomial kernel radial wavelet network method, d is the distance between the transmitter and receiver and A is the received power at a one-meter distance. Attenuation clustering radio environment estimates the path loss exponent (n) value.

$$\frac{\sum_{\mathrm{i}}^{\mathrm{m}} 1\{(\mathrm{KHm}(\mathrm{d_i}) - \mathrm{KHm}(\mathrm{d_i}))(\mathrm{a_i} - \mathrm{a_i})\}}{\sum_{\mathrm{i}}^{\mathrm{m}} 1(\mathrm{a_i} - \mathrm{a_i})^2} \quad (5)$$

$$\mathrm{a_i} = 10\log_{10(\mathrm{d_i})}(a_r(f)) \quad (6)$$

Where m is the number of measurement points, n is the path loss exponent; KHm is the measured path loss, and $(\mathrm{a_i} - \mathrm{a_i})^2$ is the average measured path loss.

Then the Attenuation Clustering Radio Environment is essential for path loss models because a wireless network design requires a specific size and shape of the areas covered by the access points. To this end, the link budget is performed:

$$K_{Qx} = K_{Dx} + K_{Px} + K_{Vx} - (A_{TX} + A_{RX} + A) \quad (7)$$

where K_{Qx} is the received power, K_{Dx} is the broadcast power, K_{Px} is the power gain of the transmitting antenna, K_{Vx} is the power gain of receiving antenna, A_{TX} is transmitting antenna cable attenuation, A_{RX} is receiving antenna cable attenuation, A is the route of EM wave propagation attenuation.

The most difficult to determine part of the link budget is the attenuation loss A of the Propagation route. If the wireless systems environment is located in an undulating area and irregular terrain or dense building structure. In such conditions, the mechanism of propagation of the EM waves is very complex. The designation of the attenuation of a route in such conditions is extremely difficult to predict. The multipath creates the most difficult problem in the digital broadcast environment which is explained in the next subsection using the novel technique Arid-Terrain-Ridge Based Integrational Radio Sensor Network.

Arid-Terrain-Ridge Based Integrational Radio Sensor Network

The radio wave propagation environment is analysed using environmental characteristics collected from the restricted environmental kinds, which replaces the complicated 3D environment modelling.

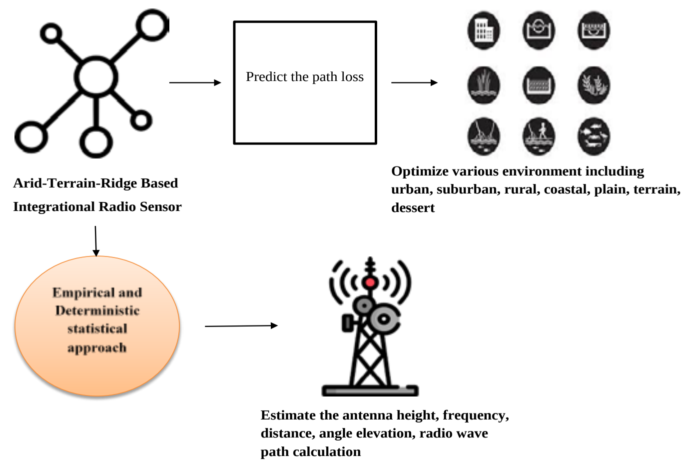

Figure 3: Architecture diagram of Arid-Terrain-Ridge Based Integrational Radio Sensor Network

Figure 3 represents the Architecture diagram of an Arid-Terrain-Ridge Based Integrational Radio Sensor Network to get good stability of RSSI in various environmental effects such as urban, suburban, rural, hilly, plain, and desert areas. Also, the Deterministic and Empirical statistical approach is utilized to analyze the propagation of radio waves in the environment taking into account the mechanisms described above and used to estimate the field strength (or signal power) directly from the path profile (profile of the terrain between the transmitter and the receiver). These methods adjust the terrain elevation to take account of the earth's curvature and are intended to provide estimations of field strengths (or power) and knowledge of the terrain profile.

Moreover, diverse environmental variables and information combinations are employed to create multiple datasets to train and assess path loss prediction models. Deterministic models, also called geometrical models, estimate the field strength (or signal power) directly from the path profile. These methods adjust the terrain elevation to take account of the earth's curvature. In addition to free space losses, these models also take account of losses due to diffraction in cases where there is insufficient clearance between the radio path and the terrain (or structures on the terrain). Site-specific geometry information is essential for the dielectric properties of materials and other terrain factors. Time-consuming computation procedure again once the propagation environment has changed.

Arid-Terrain-Ridge Based Integrational Radio Sensor Network was designed to predict the path loss values for heterogeneous networks, in which several frequencies and environments include urban, suburban, and rural. Also, used for predicting radio-wave path loss values in suburban environments.

$$y(k,\sigma) = \sum_{i=0}^{G} x_t(k) \exp\{q\tau_t(k)\} \gamma\{\sigma - \sigma_t(k)\} \quad (8)$$

In Equation (8) where k, σ are the observation and application times of the impulse, respectively; $x_t, \tau_t, and\ \sigma_t$ are the time-varying amplitude, propagation delay, and phase shift, various environments, dry place, wet place of the t[th] multipath component respectively; and G is the number of multipath components of the channel of interest.

Then the Empirical models (also called statistical) were originally intended to provide estimations of field strengths (or power) in cases where there was insufficient knowledge of the terrain profile. These models were developed from data obtained from extensive measurements in different environments. Empirical models mainly rely on measurements in a given frequency range.

Parameters of empirical models are extracted from measured data. Empirical models can only represent the path loss statistics at a given distance.

In Equation (9) empirical data to determine path loss (KHm) for a typical environment according to the value of environmental correction factor (CA)

$$\text{KHm}\ (dB) = A + Blog_{10}d + CA \quad (9)$$

Where,

$$\mathrm{A} = 69.55 + 26.16.\log_{10}\ (\mathrm{f})\ \_13.82.\log_{10}(\mathrm{h_b}) - \mathrm{a}(\mathrm{h_m})$$
$$B = 4.9 - 6.55.log_{10}\,(h_b)$$

The h_b is the antenna height in meters and f is the frequency in MHz The correction factors $a(h_m)$ are for the antenna height h_m in meters and d is the distance in meters.

Equation (10) is utilized to calculate the urban area CA=0 for medium – small city

$$\mathrm{a}(\mathrm{h_m}) = (1.1.\log_{10}(\mathrm{f}) - 0.7).\mathrm{h_m} - (1.56.\log_{10}\,(\mathrm{f}) - 0.8) \quad (10)$$

Equation (11) is utilized to calculate large city (f>400MHz)

$$a(h_m) = 8.29.(\,log_{10}\,1.54.h_m)^2 - 1.1 \quad (11)$$

Equation (12) is utilized to calculate the suburban area.

$$\mathrm{CA} = -2.(\log_{10}\left(\frac{\mathrm{f}}{28}\right))^2 - 5.4 \quad (12)$$

Equation (13) is utilized to calculate the open area.

$$\mathrm{CA} = 4.78.(\log_{10}\,(\mathrm{f}))^2 + 18.33.\log_{10}(\mathrm{f}) - 40.94 \quad (13)$$

$$PL = 92.4 + 20log(d) + 20log(f) + 20.41 + 9.83log(d) + 7.89log(f) + 9.56(log(f))^2 + log\left(\frac{h_b}{200}\right)(13.958 + 5.8.log(d))^2 + G \quad (14)$$

Equation (14) is utilized to calculate the path loss. Empirical models are utilized for the dependency on cartographic data and are only valid for short frequency ranges and different contexts such as urban, suburban, open, plain, desert, rural, marine, and so on, and to analyze the propagation of radio waves in the environment taking into account the mechanisms described above and used to estimate the field strength (or signal power) directly from the path profile (profile of the terrain between the transmitter and the receiver). These methods adjust the terrain elevation to take account of the earth's curvature and are intended to provide estimations of field strengths (or power) and knowledge of the terrain profile.

Overall, the designed model polynomial kernel radial wavelet network in which the attenuation clustering radio environment properly selects the appropriate parameters in a radio telecommunication network. Arid-terrain-ridge based integrational radio sensor network in which the deterministic and empirical statistical approach utilized for the selection of various parameters such as radio wave path calculation, frequency, antenna heights, distance, and angle elevation are analyzed accurately with environments such as urban, suburban, sea, rural, desert, hilly, terrain and with good stability and predications of RSSI.

RESULTS AND DISCUSSION

This section includes a thorough discussion of the implementation results, as well as the performance of the designed system and a comparison section to ensure that the designed system is applicable for Radio Network TETRA Path Loss Calculation by Deterministic, Empirical, and Polynomial Kernel Radial Wavelet Network Models for RSSI Predication and Comparison in Undulating Area.

System configuration

The designed system is simulated in python, and this section provides a detailed description of the implementation results and the performance of the designed system and a comparison section to ensure that the designed system performs valuable.

This work has been implemented in the working platform of Python with the following system specification and the simulation results are discussed below.

OS : Windows 10
software : Python
RAM : 8 GB RAM
Processor : Intel i5

Simulated output of designed model

Table 1 represents the parameters and the value used in the designed model, such as base station transmits power (*Pt*), Frequency, Handheld transmit power, Mobile station dynamic range, Shadow fading correlation, Standard deviation for the Shadow, MS/BS noise figures, Transmitter tower height, Channel profile, Transmission antennas (*GBS*), Handheld antennas (*GCPE*), Handheld speeds.

Table 1: Parameters used in the model

Parameter	Value
Base station transmit power (*Pt*)	20 W
Frequency	455MHz
Handheld transmit power	300 mW
Mobile station dynamic range	70 dB
Shadow fading correlation	50%
Standard deviation for the Shadow	6 dB
MS/BS noise figures	7 dB/5 dB
Transmitter tower height	60 feet
Channel profile	ITU vehicular
Transmission antennas (*GBS*)	65° / 17 dBi
Handheld antennas (*GCPE*)	Omni / 1.5 dBi
Handheld speeds	0.3 km/h and 50 km/h

Figure 4: Geographical location of the designed model

Figure 4 represents Lavasa's smart city areas selected to obtain the measurements. The measurements were conducted during the daytime. The site is geographically located at latitude (N18 25 34.9) north of the equator and longitude (E73 31 25.3) east of the prime meridian on the map of INDIA base stations were selected within the area of LAVASA.

Figure 5 represents the measurement system consisting of a Laptop with Test Equipment Signal Hound BB60C investigation software installed, a Tetra handset with pocket software installed, and a GPS receiver.

Figure 5: Measurement system of the designed model

Performance metrics of the designed system

This section provides a detailed explanation of the suggested technique's effectiveness and the result.

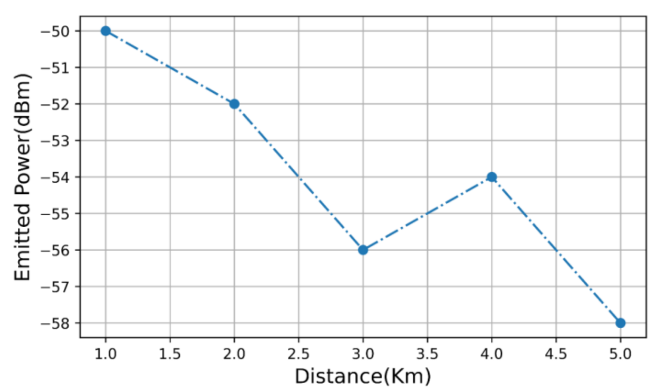

Figure 6: Emitted power of the designed model

The emitted power of the designed system for varying the number of input samples has been shown in figure 6. In the TETRA radio network, the transmitted power is proportional to the distance between the transmitter and the receiver. The emitted power of the designed system achieves a maximum value of -50 (dBm) when the distance (Km) is reduced and attains a minimum value of -58 (dBm) when the distance (Km) is increased. This connection emphasizes the dynamic adjustment of emitted power depending on shifting distances within the TETRA network, with the goal of maintaining the required signal intensity for optimal communication, particularly in undulating terrain where topographical variations impair signal propagation.

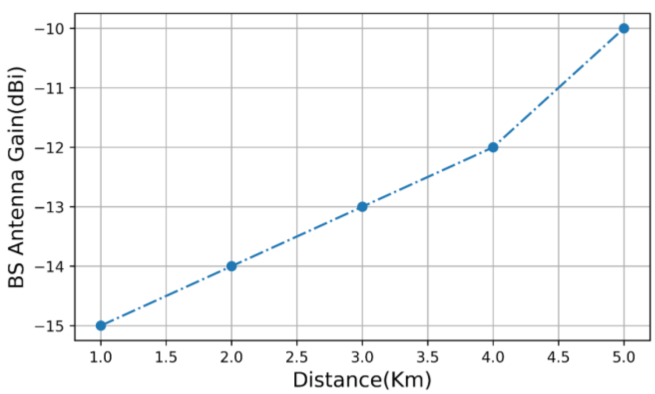

Figure 7: BS Antenna Gain of the designed model

The BS Antenna Gain of the designed system for varying the number of input samples has been shown in figure 7. The BS Antenna Gain of the designed system achieves a maximum value of -10 (dBm) when the number of distance (Km) is reduced and attains a minimum value of -15 (dBm) when the number of distance (Km) is increased. The designed Polynomial Kernel Radial Wavelet Network approach reduces BS Antenna Gain by considering comprehensive characteristics such as radio wave route, frequency, antenna heights, distance, and angle elevation. It accomplishes this by accurately assessing the value of route loss, resulting in increased system performance and optimized network resource allocation.

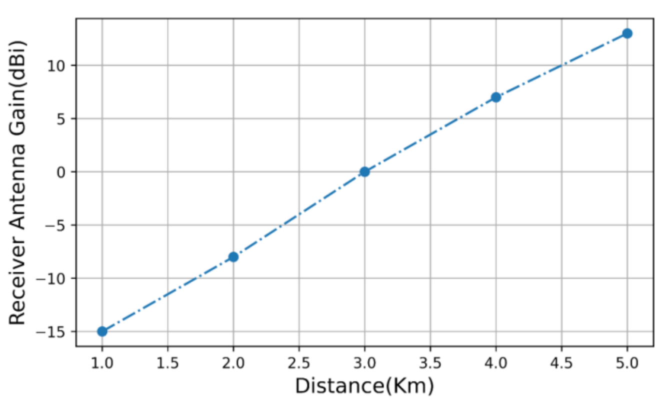

Figure 8: Receiver Antenna Gain of the designed model.

The receiver antenna gains of the designed system for varying the number of input samples have been shown in figure 8. The receiver antenna gain of the designed system achieves a maximum value of 10 (dBm) when the distance (Km) is increased and attains a minimum value of -15 (dBm) when the distance (Km) is reduced. The receiver antenna gain of the designed system has been reduced because of the novel technique Polynomial Kernel Radial Wavelet Network by computing the parameter of distance. As the distance between the transmitter and receiver increases, the signal spreads across a greater region, resulting in a lower power density, which is often adapted to increasing the receiving antenna gain to maintain a proper signal-to-noise ratio.

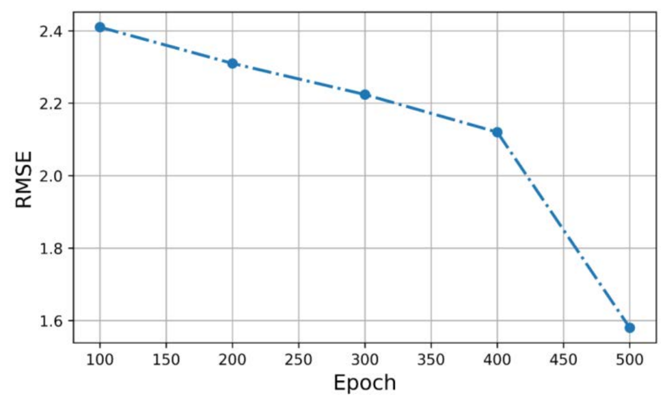

Figure 9: Root Mean Square Error of the designed model.

The root mean square error of the designed system for varying the number of input samples has been shown in figure 9. The root mean square error of the designed system achieves a maximum value of 2.4 when the number is reduced and attains a minimum value of 1.59 when the number is increased. The Radio Network TETRA Path Loss Calculation employs statistical polynomial kernel and radial wavelet network models to forecast RSSI values; by combining these models, the RMSE in undulating areas is minimized. This combination allows for more exact and trustworthy RSSI forecasts, reducing the total difference between projected and real RSSI values.

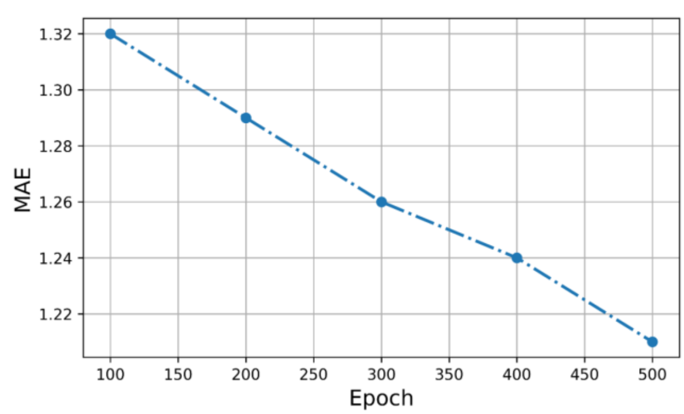

Figure 10: Mean Absolute Error of the designed model.

The mean absolute error of the designed system for varying the number of input samples has been shown in figure 10. The mean absolute error of the designed system achieves a maximum value of 1.32 when the number is reduced and attains a minimum value of 1.21 when the number is increased. The PKRWN models efficiently manage fluctuations and uncertainties in the RSSI data by including statistical analysis inside the framework, resulting in a more robust prediction of route loss. This robustness serves to reduce the MAE, which improves the accuracy of the TETRA route loss computation in undulating regions.

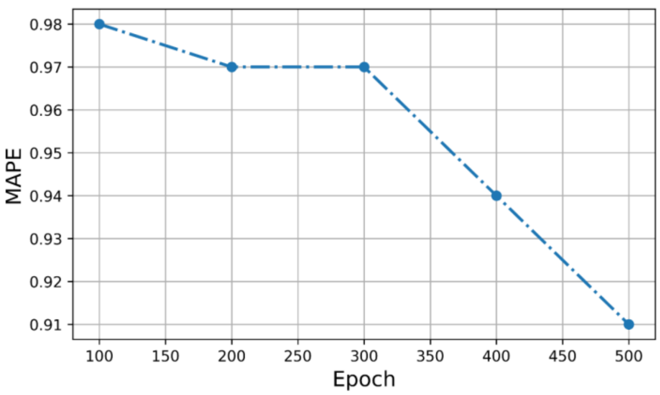

Figure 11: Mean Absolute Percentage Error of the designed model.

The mean absolute percentage error of the designed system for varying the number of input samples has been shown in figure 11. The mean absolute percentage error of the designed system achieves a maximum value of 0.98 when the epochs number is reduced and attains a minimum value of 0.91 when the number is increased. The integration of the radial wavelet network, which successfully captures both local and global fluctuations in the signal propagation environment, is the designed approach for reducing MAPE. It allows for a more accurate representation of the complicated path loss features in undulating terrain, resulting in a decrease in MAPE by successfully minimizing the errors associated with classic path loss models in such circumstances.

Comparison of Designed Model with Previous Models

This section emphasizes the effectiveness of the designed model by comparing it with the outcomes of existing methodologies and illustrating their outcomes based on several metrics. The comparisons are made from the previous techniques with the various Mean Absolute Errors, Root Mean Square Errors, Mean Absolute Percentage Errors, and Path loss. Comparisons are made with the existing techniques such as AdaBoost, Random Forest, Support Vector Machine (SVM), and Back-propagation Neural Network.[25]

Figure 12 compares the designed model's Mean Absolute Error with existing techniques such as AdaBoost, Random Forest, SVM, and Back-propagation Neural Network.

Whereas the comparison of mean absolute error attains a maximum value of AdaBoost, Random Forest, SVM, and BPNN are 6.6, 6.0, 4.0, and 3.2 respectively. The designed model has a lower mean absolute error of 3.0 than existing models even though the number of nodes increased. As a result, it is noticed that the designed system has the lowest mean absolute error by using Deterministic and Empirical statistical approaches.

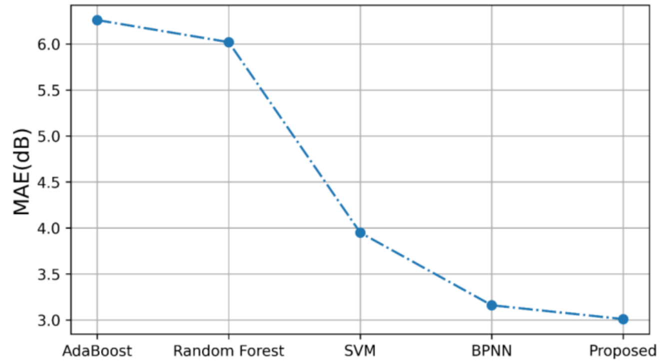

Figure 12: Comparison of Mean Absolute Error

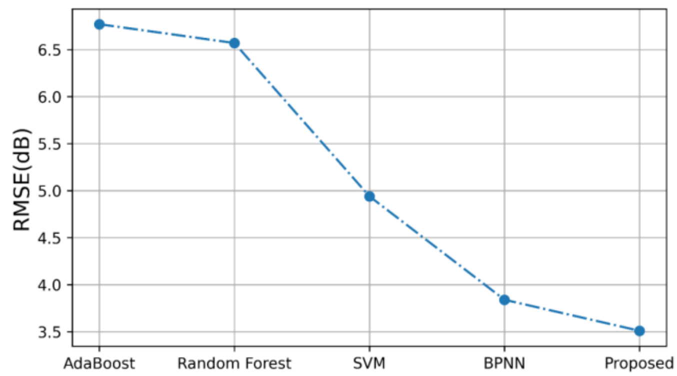

Figure 13: Comparison of Root Mean Square Error

Figure 13 compares the designed model's Root Mean Square Error with existing techniques such as AdaBoost, Random Forest, SVM, and Back-propagation Neural Network. Whereas the comparison of root mean square error attains a maximum value of AdaBoost, Random Forest, SVM, and BPNN are 6.8, 6.5, 5.0, and 3.7 respectively. The designed model has a lower root mean square error of 3.5 than existing models even though the number of nodes increased. As a result, it is noticed that the designed system has the lowest root mean square error by using Deterministic and Empirical statistical approaches.[25]

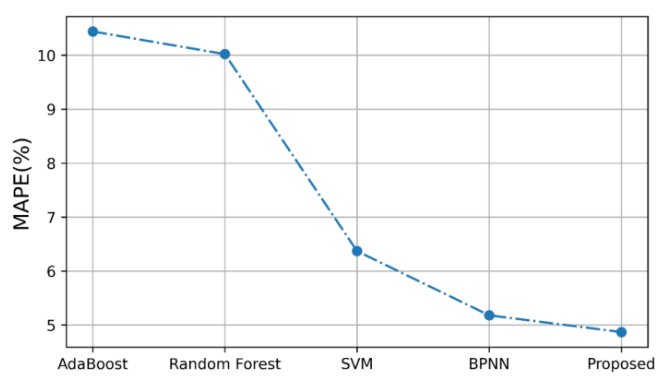

Figure 14: Comparison of Mean Absolute Percentage Error

Figure 14 compares the designed model's Mean Absolute Percentage Error with existing techniques such as AdaBoost, Random Forest, SVM, and Back-propagation Neural Network. Whereas the comparison of mean absolute percentage error attains a maximum value of AdaBoost, Random Forest, SVM, and BPNN are 10.8, 10, 6.3, 5.2 respectively. The designed model has a lower mean absolute percentage error of 4.8 than existing models, even though the number of nodes increased. As a result, it is noticed that the designed system has the lowest mean absolute percentage error by using arid-terrain-ridge based integrational radio sensor network.

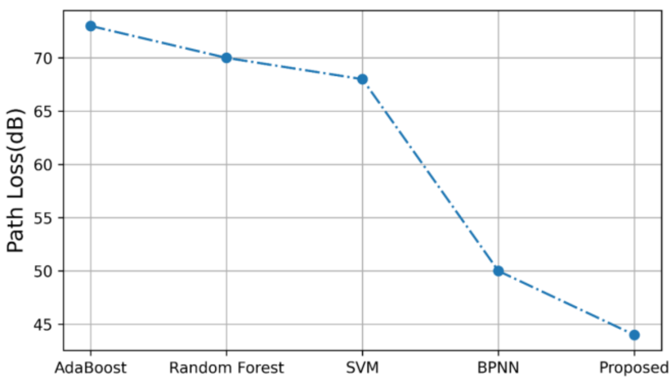

Figure 15: Path Loss comparison

Figure 15 compares the designed model's Path Loss with existing techniques such as AdaBoost, Random Forest, SVM, and Back-propagation Neural Network. Whereas the comparison of path loss attains a maximum value of AdaBoost, Random Forest, SVM, and BPNN are 10.8, 10, 6.3, and 5.2 respectively. The designed model has a lower mean absolute percentage error of 4.8 than existing models even though the number of nodes increased. As a result, it is noticed that the designed system has the lowest mean absolute percentage error by using arid-terrain-ridge-based integrational radio sensor network.

The table 2 shows the comparison of the designed model with the existing models such as AdaBoost, random forest, SVM, and BPNN, compared with existing models the designed model achieves a low MAE of 3%, RMSE of 3.5%, MAPE of 4.8%, and path loss of 4.8%.

Table 2: Comparison table of various models

Techniques	MAE	RMSE	MAPE	Path loss
AdaBoost [25]	6.6	6.8	10.8	10.8
Random Forest [25]	6.0	6.5	10	10
SVM [25]	4.0	5.0	6.3	6.3
BPNN [25]	3.2	3.7	5.2	5.2
Designed	3.0	3.5	4.8	4.8

Overall, the designed model shows that it is more efficient to predict path loss when compared to other existing techniques such as AdaBoost, Random Forest, SVM, and BNPP. The designed Radio Network Path Loss Prediction based on the Polynomial Kernel Radial Wavelet Neural Network has a low path loss of 45dB, low Mean Absolute Percentage Error (MAPE) of 4%, low Root Mean Square Error (RMSE) of 3.5dB and low Mean Absolute Error of 3.0 dB. The overall performance of the designed model outperforms all existing models.

Conclusion

To Predict the RSSI and optimize the path loss in radio networks in various environments, a novel Radio Network TETRA Path Loss Calculation by Polynomial Kernel Radial Wavelet Network Models for RSSI Predication and Comparison in Undulating Area has been designed and enhanced for TETRA path loss calculation by deterministic, empirical RSSI Predication and Comparison in Undulating Area and effectively select the parameters in different environment. The designed model utilizes the artificial intelligence model namely Polynomial Kernel Radial Wavelet Network to select the appropriate parameters and to compute the parameters such as radio wave path, frequency, antenna heights, distance, angle elevation to estimate the value of path loss. Arid-Terrain-Ridge Based Integrational Radio Sensor Network was designed to predict the path loss values for heterogeneous networks, in which several frequencies and environments include urban, suburban, and rural. Also, used for predicting radio-wave path loss values in suburban environments using propagation loss prediction model. The data is gathered from the empirical and deterministic statistical approach model. Also used to anticipate radio-wave route loss values in suburban settings and Model for predicting loss propagation. The overall performance of the designed model outperforms all existing models. Thus, the designed model attains more efficient results in predicting path loss compared to other existing techniques such as AdaBoost, Random Forest, SVM, and BNPP. The designed Radio Network Path Loss Prediction based on Polynomial Kernel Radial Wavelet Neural Network has a low path Loss of 45dB, low Mean Absolute Percentage Error (MAPE) of 4%, low Root Mean Square Error (RMSE) of 3.5dB and low Mean Absolute Error of 3.0 dB.

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