FUDMA Journal of Engineering and Technology
ISSN: 3092-9385
https://fjet.fudutsinma.edu.ng/index.php/fjet/
Volume 2, Issue 2, 2026, 283-291

Model Selection for Path Loss Prediction of Ultra High Frequency Terrestrial Television

Ayodele S. OLUWOLE[1*], Olumayowa A. OJO[2], Olaitan AKINSANMI[3]

[1*]Department of Electrical and Electronics Engineering, Federal University, Oye Ekiti, Ekiti State, Nigeria.
[2]Department of Electrical and Electronic Engineering, Bamidele Olumilua University of Education, Science and Technology Ikere-Ekiti, Ekiti State, Nigeria
[3]Department of Electrical and Electronics Engineering, Federal University, Oye Ekiti, Ekiti State, Nigeria.

[1*]asoluwole@gmail.com, [2]olumayowasolvefix@gmail.com, [3]olaitan.akinsanmi@fuoye.edu.ng

Abstract
Precise prediction of path loss is crucial for the reliable operation and optimal coverage of terrestrial Ultra High Frequency (UHF) television networks. Traditional models tend to have limited accuracy in complex propagation environments due to the fixed parameter assumptions and the lack of consideration of the nonlinear interactions among terrain, vegetation and antenna characteristics. This paper investigates the applicability of different machine learning models for the prediction of path loss in terrestrial UHF television networks. Received signal strength was first measured in the field at selected locations along five different routes in Ekiti State, Nigeria. The measured dataset was subsequently preprocessed and prepared for machine learning analysis. Five supervised machine learning algorithms were implemented and trained on the dataset, such as Linear Regression, K-Nearest Neighbors Regression, Random Forest Regression, Decision Tree Regression and Extra Tree Regression. Lastly, , the performance of the models was assessed using root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2). The results showed that KNN Regression had the lowest MAE (1.721), MSE (4.667) and RMSE (2.160) with an accuracy of 94.80%. Random Forest Regression was next with a slightly higher MAE (1.733), MSE (6.775) and RMSE (2.603), but scored the highest accuracy (94.89%) as a balanced and reliable performance overall. The results validate random forest as optimal and reliable path loss prediction model in UHF terrestrial broadcast networks. Carefully selection of machine learning models helps achieve precise estimation of path loss.

Keywords*: Model selection, path loss prediction, supervised machine learning, Random-forest, performance metrics.*

1.0 Introduction

Terrestrial television broadcasting remains among the most crucial means of information dissemination worldwide [1]. The rapid evolution of terrestrial broadcasting systems and the sustained relevance of Ultra High Frequency (UHF) television networks have intensified the necessity of precise radio propagation modeling [2]. In UHF terrestrial television systems, signal propagation is influenced by complex interactions among transmission distance, frequency, antenna heights, terrain morphology, vegetation, and man-made structures [3]. These interactions introduce significant variability and nonlinearity into the propagation channel, making reliable path loss modeling a challenging task. Path loss is the reduction in power density of an electromagnetic wave as it travels over space. Propagation mechanisms such as reflection, diffraction, scattering, shadowing, and multipath effects are major contributors to path loss, which directly impacts the power of the received signal and the quality of television reception [3], [4].

The estimation of path loss has traditionally been done using empirical and deterministic propagation models such as Free Space Path Loss (FSPL), Okumura-Hata, COST-231 Hata, Close-In (CI), Floating Intercept (FI), and Egli models [4], [5]. These models are obtained from generalized measurement campaigns and rely on fixed parameter assumptions that limit their adaptability to diverse geographical and environmental conditions [5]. Consequently, their prediction accuracy drops when applied to location-specific UHF broadcast environments, particularly in regions with heterogeneous terrain and dense clutter [6]. Different from the traditional empirical models, machine learning (ML) methods can learn the nonlinear relationships from the measured data and adapt to various environmental changes [7]. A recent study [8] showed that machine learning path loss models provide more accuracy than empirical models and are even more computationally efficient than deterministic ones. For drive test measurements carried out in Nigeria based on a marked route in the 1800 MHz frequency band coverage to obtain path loss data, the use of artificial neural networks (ANN) models evaluated for performance based on the mean absolute error (MAE), RMSE, and standard deviation metrics produced the lowest error when compared to the empirical models. [9]. Supervised learning algorithms have demonstrated strong potential in wireless channel modeling by learning implicit relationships between propagation parameters and path loss without relying on rigid analytical assumptions [7], [10].

Received: 12/06/2026; Revised: 26/07/2026 Accepted: 27/07/2026; Published: 21/08/2026

Despite the increasing body of literature applying machine learning to radio propagation prediction, several challenges remain unresolved. First, many existing studies focus on cellular or millimeter-wave frequency bands, with limited attention given to UHF terrestrial television broadcasting, which exhibits distinct propagation characteristics [9]. Second, the problem of systematic model selection by identifying the most suitable machine learning algorithm based on quantitative performance metrics has not been sufficiently addressed [10]. In many cases, model choice is arbitrary or based on limited comparisons, reducing the practical applicability of the results.

This study identified the most suitable machine learning model for terrestrial UHF television path loss prediction with measurement data. It compares the performance of linear regression, decision tree regression, extra trees regression, k-nearest neighbors, and random forest regression using statistical performance metrics such as root mean square error (RMSE), mean absolute error (MAE), and accuracy.

2.0 Materials and Methods

A Digital Field Strength Meter Radio Frequency (RF) Explorer Handheld Spectrum Analyzer was utilized to test field strength along different routes around the state. The elevation, geographic coordinates, and line of sight of the various data points from the base station were obtained using an eTrex 30 Garmin GPS receiver
The different methodology used for effective implementation of this work were as presented in Figure 1.

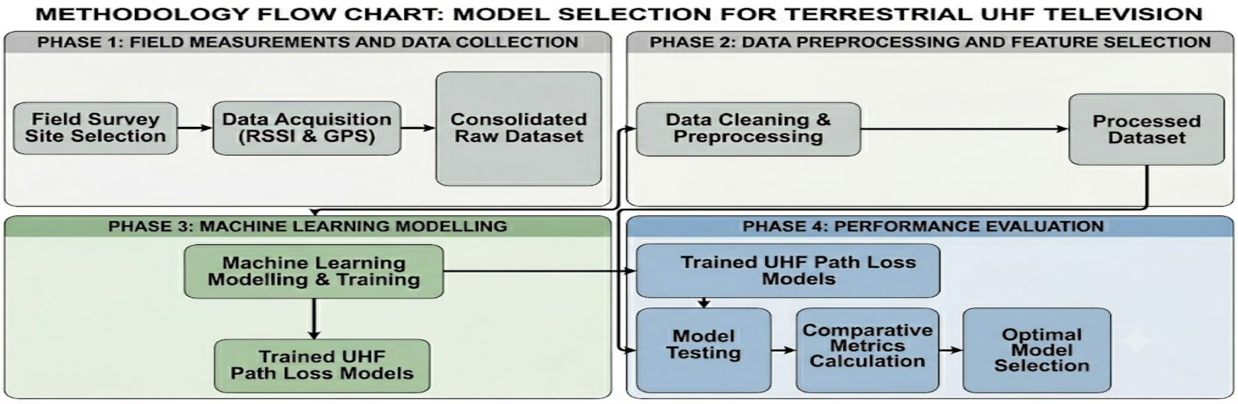

Figure 1: Operational flowchart

2.1 **Environment Measurement and Data Acquisition**

Field tests were undertaken from two terrestrial Ultra High Frequency (UHF) television broadcast network (Ekiti State Television and Star-times), gathering realistic propagation data for model selection. Measurements were taken along numerous receiver locations distributed throughout urban and suburban terrains reflective of typical broadcast coverage settings. At each measurement site, the received signal strength (RSS) was recorded using an RF Explorer Handheld Spectrum Analyzer. The geographic coordinates of each location were logged using a Global Positioning System (GPS) receiver to determine the transmitter–receiver separation distance. Measurements were conducted under stable air conditions to reduce short-term fading effects. Secondary data were acquired from the public domain to boost machine learning modelling.

2.2 Feature Selection and Data Preprocessing

Path loss prediction was formulated as a supervised regression problem. Input features were selected based on their relevance to large-scale propagation characteristics and included transmission distance, operating frequency, transmitter and receiver antenna heights, and measured RSS. Prior to model training, the dataset was preprocessed to improve learning stability and generalization. Outliers arising from measurement errors were identified and removed using statistical thresholding. Feature normalization was applied to scale the input variables to a common range, preventing dominance of features with large numerical values. The dataset was randomly divided into training and testing subsets to facilitate an unbiased evaluation of the model's performance.

2.3. Machine Learning Modelling

The following supervised machine learning approaches were used for path loss prediction.

i. Linear Regression (LR): A supervised machine learning was used to predict the association between a dependent variable (output) and one or more independent variables (inputs).
ii. Decision Tree (DT): A regression tree model that iteratively partitions the feature space into discrete sub-regions according to the splitting criteria.

Received: 12/06/2026; Revised: 26/07/2026 Accepted: 27/07/2026; Published: 21/08/2026

iii. Random Forest (RF) is an ensemble learning method that constructs several decision trees during training and outputs the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. It was used for classification and regression tasks.
iv. Extra Trees (ET) is an ensemble learning method that involves constructing a number of decision trees and then aggregating their predictions. This is similar to random forest but with more randomness in the creation of the trees.
v. K-Nearest Neighbors (KNN) is a supervised learning technique used to predict the output for a new data point by looking at the outputs of the nearest neighbors of that data in the training set.

Pre-processed training data set was used to train models. To improve the generalization ability, k-fold cross validation was employed for validation.
The model deployment from machine learning classification algorithms was attached.

2.5. Performance Evaluation Metrics

Performance of the machine learning models was carried out in making predictions on the unknown test datasets. The metrics used for measuring the performance include:
(i) Mean Absolute Error (*MAE*): It was calculated by taking the average of absolute error obtained by subtracting real values from predicted values. The Mean Absolute Error was calculated using equation 1.

$$MAE = \frac{\sum_i^n | y_i - y |}{n} \quad (1)$$

Where y_i is predicted values, y s real value and n is number of test data
(ii) Mean Squared Error (*MSE*): It is similar to *MAE* but the error for each record is squared as contained in equation 2.

$$MSE = \frac{1}{n}\sum_i^n (y_i - y)^2 \quad (2)$$

(iii) Root Mean Squared Error (*RMSE*): It is calculated by finding the square root of *MSE* as stated in equation 3.

$$RMSE = \sqrt{\frac{1}{n}\sum_i^n (y_i - y)^2} \quad (3)$$

(iv) Accuracy: The accuracy of the model is obtained by subtracting the mean value of MAPE of test data from 100.as stated in 5

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y_i}}{y_i}\right| \quad (4)$$

Accuracy = (100 – MAPE) % (5)

These performance metrics were implemented using Python software as presented as "Program for Evaluating Model Performance"

3.0 Results and Discussion

3.1 Field measurements and Data Collection.

Table 1 presents the field measurement along route A from the EKTV and Star-times basestation indicating the different parameters recorded. The field strength measurements taken along a specific path, designated as "Route A," originating from EKTV Base station. There is a general trend of signal weakening with increasing distance from base station. There were field strength variations as some mid-range locations show stronger signals than expected (Oye, Ilupeju). There was a mixed impact of elevation some high points yield strong signal, others do not. Sharp drop to 15 dBμV suggests obstruction, interference, or NLOS condition. This underscores the importance of site-specific analysis for radio network planning; distance alone cannot predict signal behavior accurately. The results of field strength measurements taken along a specific path, designated as "Route A," originating from a Star-times Base station was presented in Table 2. Signal strength generally declined as distance increases, reaching a low of 15.5 dBμV at 38.18 km (Ikole). At Ilupeju (25.94 km) there was a sharp drop of signal strength to 20.5 dBμV, despite the highest elevation (622 m), showing that elevation alone does not guarantee good signal. Signal strength is influenced more by line-of-sight and local terrain than just distance or elevation.

Table 1: Field measurement along Route A from EKTV Base station.

Observation	Line of Sight from EKTV Base (km)	Latitude (Degrees)	Longitude (Degrees)	Elevation (AGL) (m)	Field Strength E (dBμV)	Location
1	0.00	7.8019	5.45972	373	93.5	Base
2	2.44	7.93306	5.42833	399	64	Eksu Gate

Received: 12/06/2026; Revised: 26/07/2026 Accepted: 27/07/2026; Published: 21/08/2026

Observation	Line of Sight from EKTV Base (km)	Latitude (Degrees)	Longitude (Degrees)	Elevation (AGL) (m)	Field Strength E (dBµV)	Location
3	5.31	7.79056	5.38833	408	47.5	Eksu 2
4	6.56	7.97556	5.41861	427	48.5	Iworoko
5	11.39	7.94028	5.45639	569	39.5	Ifaki Ekiti
6	12.61	7.86083	5.39361	556	37.5	Ifaki Ekiti
7	14.11	7.95500	5.41556	543	33	Ayegbaju
8	16.64	7.82833	5.48222	550	45.5	Oye
9	18.48	7.98472	5.53361	618	48.5	Ilupeju
10	21.80	7.99667	5.53361	611	36.5	Itapa
11	23.14	7.84417	5.60028	519	15	Osin
12	31.35	7.86722	5.54972	565	33.5	Ikole
13	31.93	7.91194	5.69833	563	31.5	Ikole

Table 2: Field Measurement along Route A from Star-times Base station

Observation	LOS EKTV Base (Km)	Latitude (Degrees)	Longitude (Degrees)	Elevation AGL(m)	Field Strength E (dBµV)	Location
1	0.00	7.86528	5.35889	478	66	Base
2	5.63	7.85611	5.44111	415	54	Fajuyi
3	11.88	7.89222	5.42528	414	44	Eksu
4	13.28	7.95389	5.42556	436	41.5	Iworoko
5	12.61	7.86083	5.39361	556	38.5	Ifaki Ekiti
6	18.47	7.95389	5.46361	578	31.5	Ifaki Ekiti
7	21.11	7.94194	5.50028	552	33	Ayegbaju
8	23.82	7.82917	5.52694	557	42.5	Oye
9	25.94	7.98222	5.52694	622	20.5	Ilupeju
10	29.38	7.98861	5.44306	609	26	Itapa
11	30.59	7.84222	5.59694	523	18.5	Osin
12	38.18	7.81194	5.68722	549	15.5	Ikole

3.1.1 Discussion on Data Collection on Path loss from Different sources

The results of data collection on path loss from other sources were presented in Table 3 while Table 4 presents correlation coefficients.

Correlation analysis was performed and statistical comparison was done to evaluate relationships between metrics in original and augmented datasets. The correlation matrices and standard deviations were calculated for both the datasets as shown in Tables 4.2 and 4.3 respectively. The statistical analysis indicates that the correlation values of the augmented dataset are very similar to the original dataset, preserving intrinsic relationships, such as the strong correlations between Distance and Path Loss, and Field Strength and Path Loss. The standard deviation of Distance and Path Loss is slightly higher in the augmented dataset as compared to the original dataset, probably due to the larger size of the dataset and noise injection. The standard deviation of Elevation and Field Strength is lower in the augmented dataset, which means that the simulated data is smoother in terms of variability. These results confirm that the statistical properties of the original dataset are mostly preserved in the augmented one with minor deviations due to the intentional effects of the interpolation and noise injection during the augmentation

Table 3: Sample of Data obtained from other sources

Distance (km)	Elevation (m)	Field Strength (dBµV)	Path loss (dB)
0	516.00	79.200	0.000
2	171.00	11.918	81.918
2	171.00	11.324	81.324
4	155.00	21.791	91.790
4	155.00	21.320	91.320
6	66.00	30.159	100.159
6	66.00	28.454	98.454
8	88.00	34.513	104.513

Distance (km)	Elevation (m)	Field Strength (dBµV)	Path loss (dB)
8	88.00	33.658	103.658
10	55.00	36.812	106.812

Table 4: Correlation coefficients between the variables for both datasets.

Metric Pair	Original Dataset Correlation	Augmented Dataset Correlation
Distance vs. Elevation	0.231	0.244
Distance vs. Field Strength	-0.854	-0.867
Distance vs. Path Loss	0.918	0.902
Elevation vs. Field Strength	-0.213	-0.201
Elevation vs. Path Loss	0.276	0.251
Field Strength vs. Path Loss	-0.924	-0.912

Table 5: Standard Deviation Values for the Study Variables

Metric	Original Dataset Std. Dev.	Augmented Dataset Std. Dev.
Distance (Km)	20.60	22.26
Elevation (M)	230.88	156.48
Field Strength	11.17	7.52
Path Loss (Db)	30.09	39.70

Results of data wrangling and preprocessing were shown in Figure 2 with the help of correlation heat map. The correlation analysis of the augmented data reveals that the distance exhibits a strong positive correlation with path loss (0.71), making it the most significant factor influencing signal attenuation. This finding aligns with propagation models, which indicate that signal loss increases as the distance between the transmitter and receiver grows. Field strength shows a strong negative correlation with path loss (-0.81), as expected in wireless communication systems. Elevation displays a very strong negative correlation with path loss (-0.99), implying that higher elevations significantly reduce signal attenuation, likely due to fewer obstructions and improved line-of-sight conditions. In general, the analysis shows the dominant role of distance in signal attenuation while emphasizing the substantial influence of elevation and field strength, which collectively shape the signal propagation characteristics of the augmented dataset. Therefore, in order to enhance the predictive accuracy, the model building was built by using three parameters as features while path loss was the target variable.

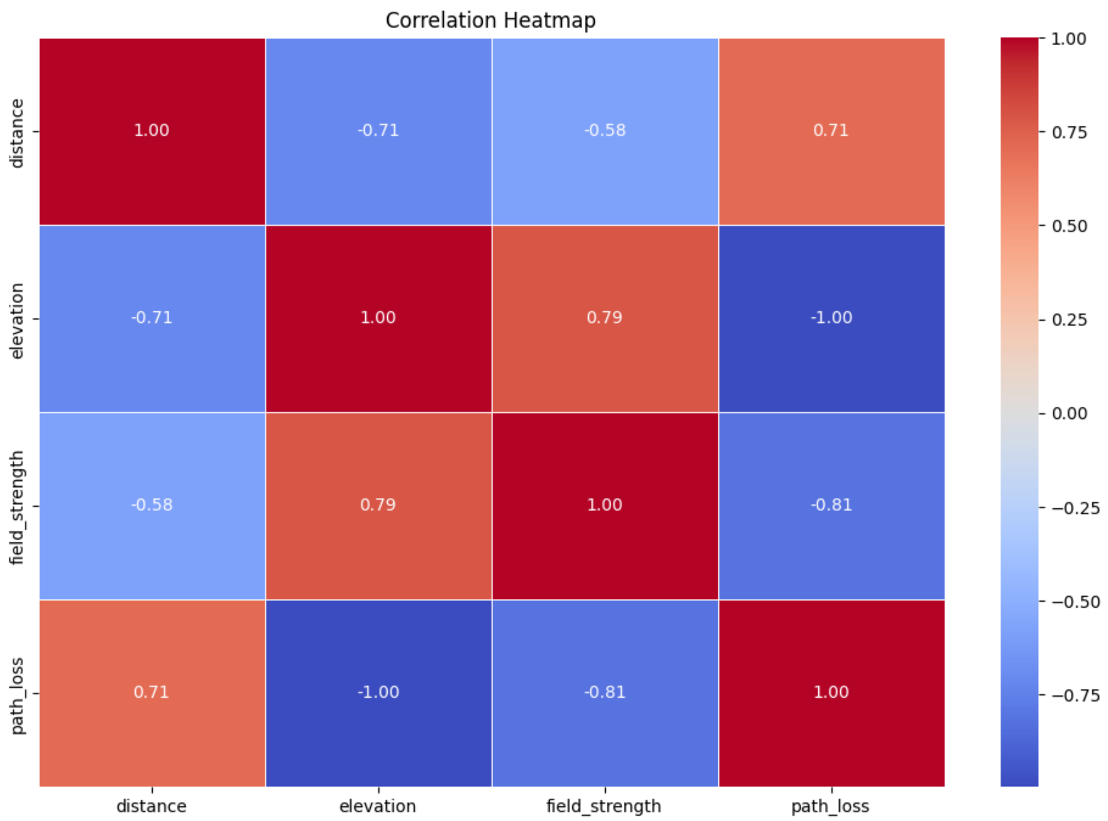

Figure 2: Correlation heat map between path loss and other variables in the dataset

Received: 12/06/2026; Revised: 26/07/2026 Accepted: 27/07/2026; Published: 21/08/2026

3.2 Performance Evaluation

The results of performance evaluation of the five machine learning models were presented in Table 6 for model selection and assessment. Table 6 contains Linear Regression, KNN Regression, Random Forest Regression, Decision Tree Regression, and Extra Tree Regression. These models were evaluated using four key metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Accuracy (%).

KNN Regression emerges as the best-performing model, exhibiting the lowest MAE (1.721), MSE (4.667), and RMSE (2.160), along with an accuracy of 94.80%. These results suggest that KNN provides the most precise and consistent predictions with fewer large errors compared to the other models. Random Forest Regression follows closely with a slightly higher MAE (1.733), MSE (6.775), and RMSE (2.603), but it achieves the highest accuracy (94.89%), indicating a balanced and reliable performance overall.

In contrast, Decision Tree Regression performs the weakest, with the highest MAE (2.352), MSE (14.427), RMSE (3.798), and the lowest accuracy (93.62%). This suggests that the model may be prone to overfitting or instability in its predictions. Linear Regression, while simple, shows the lowest accuracy (91.94%) and higher error metrics compared to the others, making it the least accurate model. Extra Tree Regression performs similarly to Random Forest and KNN but slightly lags behind in accuracy (94.68%), showing that it is also a strong contender, though not the top performer. In conclusion, though Random Forest Regression and KNN Regression are the most reliable models for this dataset, the Random Forest is the optimal model, being slightly superior in terms of accuracy.

Table 6: Performance Evaluation of the five Machine Learning Models

Model	**Mean Absolute Error**	**Mean Squared Error**	**Root Mean Squared Error**	**Accuracy (%)**
Linear Regression	2.157	7.424	2.725	91.94
KNN Regression	1.721	4.667	2.160	94.80
Random Forest Regression	1.733	6.775	2.603	94.89
Decision Tree Regression	2.352	14.427	3.798	93.62
Extra Tree Regression	1.753	4.899	2.213	94.68

3.2.1 Analysis and Discussion of Model Performance Accuracy Comparison

Random Forest Regression achieved the highest accuracy at 94.89%, closely followed by KNN Regression (94.80%) and Extra Tree Regression (94.68%). Linear Regression had the lowest accuracy at 91.94%. Most non-linear and ensemble models (KNN, Random Forest, Extra Trees) performed noticeably better than the standard Linear Regression, suggesting the data may have non-linear relationships. The model accuracy comparison is as displayed in figure 3.

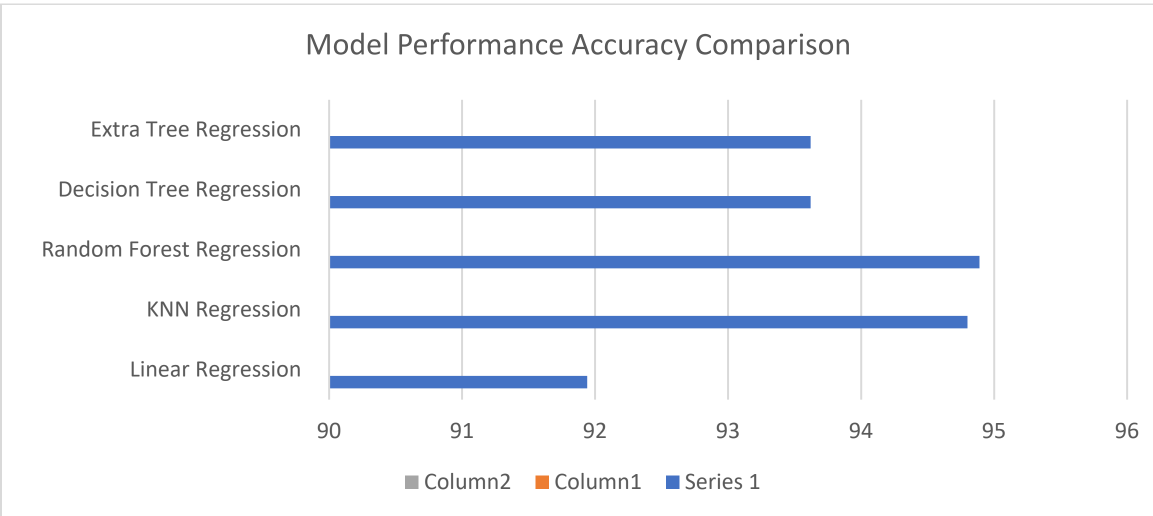

Figure 3: Model Accuracy Comparison

Received: 12/06/2026; Revised: 26/07/2026 Accepted: 27/07/2026; Published: 21/08/2026

3.2.2. Error Metrics Analysis (MAE, MSE, and RMSE)

Mean absolute error, mean squared error and root mean squared error metrics were applied for comparison. For these metrics, lower values indicate better performance. Figure 4 displays the analysis.

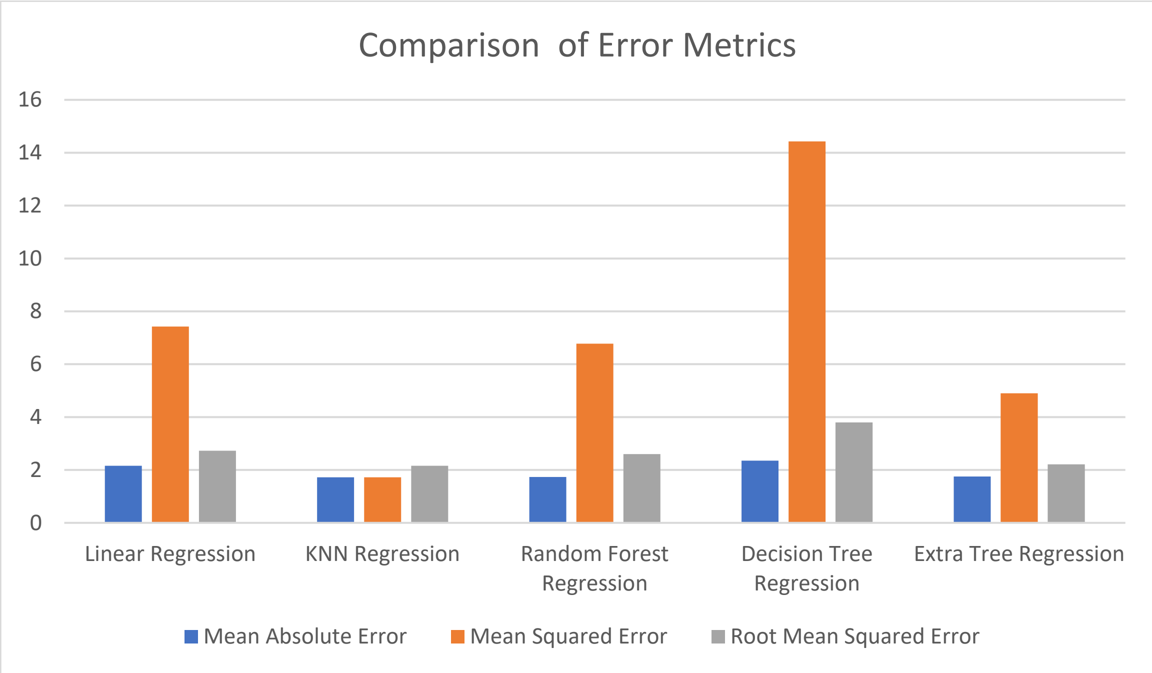

Figure 4: Comparison of Error Metrics across Machine Learning Models

Mean Absolute Error (MAE): KNN Regression has the lowest MAE (1.721), followed closely by Random Forest (1.733) and Extra Trees (1.753). Decision Tree Regression shows the highest average error magnitude (2.352).

Mean Squared Error (MSE) and Root Mean Squared Error (RMSE):

While Random Forest has the highest raw accuracy, KNN Regression shows more stability with the lowest overall error rates across all three-error metrics (MAE, MSE, RMSE), Extra Tree Regression shows very consistent performance, ranking third across almost all metrics, making it a reliable alternative to Random Forest. The decision tree regression model appears to suffer from high variance (likely overfitting or sensitivity to specific data points), as evidenced by its disproportionately high MSE compared to its accuracy. Linear Regression is likely too simple for this specific dataset, resulting in the lowest accuracy. Previous studies on random forest modelling shows that the model exhibited better generalization capability and robustness [17] Accurate path loss prediction remains a critical requirement for the effective planning, coverage optimization, and quality-of-service improvement of terrestrial UHF television broadcasting systems. Signal propagation in the UHF band is strongly influenced by several environmental and system-related factors, including terrain irregularities, vegetation, buildings, transmission distance, and antenna characteristics. These factors introduce complex and nonlinear propagation behaviors that are often inadequately captured by conventional empirical path loss models.

4.0 Conclusion

This paper examined machine learning based approaches for path loss prediction in terrestrial UHF television broadcasting environments using measured field data. The main focus of this work is the selection of an optimal machine learning model for improved prediction accuracy. The evaluated algorithms included Random Forest regression, Decision Tree regression, Extra tree regression, Linear regression, and K-Nearest Neighbor's regression. The performance of each model was assessed using standard error metrics such as RMSE, MAE, and the correlation coefficient. The results demonstrate that machine learning models significantly captured the complex propagation characteristics of UHF terrestrial television signals. Among the evaluated algorithms, the Random Forest model consistently achieved the highest prediction accuracy of 94.89% and the second lowest error values (MAE-1.733, MSE-6.775, RMSE-2.603) indicating it's that it is more reliable and balance to model nonlinear relationships and interactions among propagation parameters. This makes Random Forest a robust and reliable model for path loss prediction in UHF broadcasting environments.

Received: 12/06/2026; Revised: 26/07/2026 Accepted: 27/07/2026; Published: 21/08/2026

The main contributions of this work are summarized as follows:
(i) The development of a measurement-driven machine learning framework for UHF terrestrial path loss prediction;
(ii) A systematic comparison of multiple ML algorithms using consistent performance metrics;
(iii) The identification of an optimal algorithm based on quantitative accuracy and robustness criteria.
The overall findings of this study confirm that the careful selection of an appropriate machine learning model is essential for accurate path loss prediction in terrestrial UHF television systems. The adoption of machine learning–based models, particularly ensemble techniques such as Random Forest, can enhance network planning, improve coverage estimation, and support the optimization of broadcast infrastructure in real-world environments. Future work may extend this study by incorporating additional propagation features, hybrid modeling approaches, and cross-regional validation to further improve prediction robustness and generalization.

References

[1] O. O. Shoewu, L. A. Akinyemi, and N. T. Makanjuola, "An assessment of terrestrial television broadcasting in Nigeria: Challenges and prospects," *Journal of Advancement in Engineering and Technology*, vol. 6, no. 3, pp. 1–7, 2018.

[2] International Telecommunication Union (ITU), "Transition from analogue to digital terrestrial television broadcasting," ITU-R Handbook, Geneva, Switzerland, 2021.

[3] H. Sisayan and S. Sharma, "Analysis of radio wave propagation mechanisms and path loss in UHF bands for urban environments," *IEEE Transactions on Antennas and Propagation*, vol. 68, no. 11, pp. 7543–7552, Nov. 2020.

[4] T. S. Rappaport, *Wireless Communications: Principles and Practice*, 2nd ed. Upper Saddle River, NJ, USA: Prentice Hall, 2002.

[5] J. Isabona and S. Akinwumi, "A comparative evaluation of empirical path loss models for digital television signal propagation in UHF band," *International Journal of Wireless and Microwave Technologies (IJWMT)*, vol. 11, no. 4, pp. 23–35, Aug. 2021.

[6] N. S. Nkordah, O. F. Oseni, and A. A. Alaba, "Limitations of empirical path loss models in heterogeneous terrains for UHF broadcast bands," *IEEE Access*, vol. 9, pp. 114205–114218, 2021.

[7] J. M. Crane, L. Silva, and R. Feick, "Machine learning approaches vs. empirical models for path loss prediction in complex urban environments," *IEEE Wireless Communications Letters*, vol. 10, no. 5, pp. 982–986, May 2021.

[8] C. E. G. Moreta, M. R. C. Acosta, and I. Koo, “Prediction of digital terrestrial television coverage using machine learning regression,” *IEEE Transactions on Broadcasting*, vol. 65, no. 4, pp. 702–712, Dec. 2019.

[9] C. A. Oroza, Z. Zhang, T. Watteyne, and S. D. Glaser, “A Machine-Learning-Based Connectivity Model for Complex Terrain Large-Scale Low-Power Wireless Deployments,” *IEEE Trans. Cogn. Commun. Netw.*, vol. 3, no. 4, pp. 576–584, 2017, doi: 10.1109/TCCN.2017.2741468

[10] Y. Zhang, J. Wen, and G. Yang, "Supervised machine learning algorithms for wireless channel modeling: A comprehensive review," *IEEE Communications Surveys & Tutorials*, vol. 24, no. 1, pp. 453–481, First Quarter 2022.

[11] M. Ayadi, A. Ben Zineb, and S. Tabbane, "Radio propagation modeling for UHF terrestrial television vs. cellular networks: A comparative study on coverage and path loss," *Telecommunication Systems*, vol. 79, no. 2, pp. 215–229, Feb. 2024.

[12] S. Bakirtzis, K. Psannis, and T. Xifilidis, "On the selection metrics and systematic evaluation of machine learning models for radio frequency path loss prediction," *IEEE Transactions on Vehicular Technology*, vol. 73, no. 3, pp. 3102–3115, Mar. 2025.

[13] N. Faruk, I. Y. Abdulrasheed, N. T. Surajudeen-Bakinde, E. Adetiba, A. A. Oloyede, A. Abdulkarim, O. Sowande, A. H. Ifijeh, and A. A. Atayero, “Large-Scale Radio Propagation Path Loss Measurements and Predictions in the VHF and UHF Bands,” *Heliyon*, vol. 7, no. 6, p. e07298, Jun. 2021, doi: 10.1016/j.heliyon.2021.e07298.

[14] N. Faruk, S. I. Popoola, N. Surajudeen-Bakinde, A. Oloyede, et al., “Path Loss Predictions in the VHF and UHF Bands Within Urban Environments: Experimental Investigation of Empirical, Heuristics and Geospatial Models,” *IEEE Access*, vol. 7, pp. 77293–77307, 2019, doi: 10.1109/ACCESS.2019.2921411.

[15] H.-S. Jo, C. Park, E. Lee, H. K. Choi, and J. Park, “Path Loss Prediction Based on Machine Learning Techniques: Principal Component Analysis, Artificial Neural Network, and Gaussian Process,” *Sensors*, vol. 20, no. 7, pp. 1–20, Mar. 2020, doi: 10.3390/s20071927.

[16] S. I. Popoola, E. Adetiba, A. A. Atayero, N. Faruk, and C. T. Calafate, “Optimal model for path loss predictions using feed-forward neural networks,” *Cogent Eng.*, vol. 5, no. 1, 2018, doi: 10.1080/23311916.2018.1444345.

[17] S. Sukemi, A. F. Oklilas, M. W. Fadil, and B. Alfaresi, "Path loss prediction accuracy based on random forest algorithm in Palembang City area," Jurnal Nasional Teknik Elektro, vol 12, no. 1, pp. 23-29, 2023, doi: 10.25077/jnte.v12n1.1052.2023.

Appendix

Model deployment from machine learning regresion algorithms

```
#LINEAR REGRESSION
from sklearn.linear_model import LinearRegression
# training the algorithm
lin_model = LinearRegression()
lin_model.fit(x_train, y_train)
# making predictions on test set
y_pred_lin = lin_model.predict(x_test)
#KNN REGRESSION
from sklearn.neighbors import KNeighborsRegressor
KNN_model = KNeighborsRegressor(n_neighbors=5)
KNN_model.fit(x_train, y_train)
y_pred_knn = KNN_model.predict(x_test)
# RANDOM FOREST REGRESSION
# training and testing the random forest
from sklearn.ensemble import RandomForestRegressor
rf_reg = RandomForestRegressor(random_state=42, n_estimators=500)
rf_reg.fit(x_train, y_train)
y_pred_rf = rf_reg.predict(x_test)
DECISION TREE REGRESSION
from sklearn.tree import DecisionTreeRegressor
tdt_model = DecisionTreeRegressor()
# fit model
dt_model.fit(x_train, y_train)
y_pred_dt = dt_model.predict(x_test)

# EXTRA TREE REGRESSION
from sklearn.ensemble import ExtraTreesRegressor
xt_model = ExtraTreesRegressor(n_estimators = 10)
# Training the model
xt_model.fit(x_train, y_train)
# Make predictions
y_pred_xt = xt_model.predict(x_test)
```

Program for Evaluating Model Performance"

```
count = -1
predictions = [y_pred_lin, y_pred_knn, y_pred_rf, y_pred_dt, y_pred_xt]
regressions = ["Linear Regression", "KNN Regression", "Random Forest Regression",
"Decision Tree Regression", "Extra Tree Regression"]
for y_pred in predictions:
    count += 1
    print(".........." + regressions[count] + "..........")
    print ('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
    print ('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
    print ('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,
y_pred)))
    #Calculating mean absolute percentage error (MAPE) and Accuracy
    errors = abs(y_pred - y_test)
    mape = 100 * (errors / y_test)
    accuracy = 100 - np.mean(mape)
    print ('Accuracy: ', round(accuracy, 2), '%.')
```

Received: 12/06/2026; Revised: 26/07/2026 Accepted: 27/07/2026; Published: 21/08/2026