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Computation of VHF Signal Strength for Point to Area Network using Machine Learning Modeling Techniques

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ABSTRACT

In this paper, computation of very high frequency (VHF) signal strength for point to area network was carried out using machine learning modeling techniques. Seven different machine learning models were adopted: Decision Tree, Random Forest, AdaBoost, k-Nearest Neighbor, Support Vector Machine, Artificial Neural Network and Linear Regression. A total of 120 data points was used in computing the signal strength. 72 data points (60%) was used to train the model, while the remaining 48 data points (40%) were used as test data to determine the accuracy of the computation for all the models. From the results, it was observed that the accuracy of the computations was greatly influenced by the amount of training data that was used. Also, from the results, in highest order of accuracy, AdaBoost was adjudged the best model. This was followed by the Artificial Neural Network model. Generally, the error margin of computation obtained for these two models were low, hence indicating that the models can be effectively relied on for computation of signal strength in the study area.

1. INTRODUCTION

A very important factor that determines the performance of wireless radio communication systems is the propagating medium between the transmitter and receiver. This is because wireless radio systems are random in nature as they are dependent on atmospheric variables such as humidity, pressure, temperature, hydrometeors and atmospheric gases [1]. Generally, a statistical approach is adopted in practice for prediction of propagation effects. For effective and reliable communication between a transmitter and a receiver, knowledge of the spatial and temporal variability of field strength is required. Where a high-quality signal is desired, especially in broadcast applications, this assumes greater significance [2]. Hence, predicting the propagation of radio signals is of great significance in the design and planning of wireless communication systems [3-4].

Propagation models are very important in analysing the performance of wireless communication systems. This is also vital in assessing the quality of received signals. Until now, empirical pathloss models have been commonly used to design and plan communication systems because of their simple and less computational nature [5]. These qualities make them popular but their major disadvantage is their inaccuracies, especially when they are used in other settings different from the one where the original measurements were taken [6]. An alternative method is the use of deterministic models which seem to have better accuracy because of the comprehensive information available concerning the propagation environment. Nevertheless, this method is computationally exhaustive and time consuming [7]. Hence, the recent use of machine learning techniques. This is because machine learning approach is very efficient in handling statistical problems more accurately than the analytical methods. Therefore, signal strength computation in this paper was achieved using different machine learning techniques through the mining of atmospheric and received signal strength data propagated from a transmitter to a receiver.

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2. BACKGROUND

2.1 Predictive analytics (Orange)

Predictive analytics are used to forecast unknown future events. They employ different techniques from predictive modeling to machine learning. Different types of predictive analytic software exist for various analyses and forecasting but Orange is one of the most frequently used because of its user-friendly nature.

The development of Orange application software started in 1997 at the University of Ljubljana, Slovenia. Initially, its concept was a C++ library of machine learning algorithms but was later incorporated with Python scripting. Orange is flexible and user-friendly, with a graphical user interface and visual programming environment, it is one of the easiest data mining tools to use. Windows and Linux are among the Operating Systems it runs on. It comprises several machine learning, preprocessing and data visualisation algorithms [8]. In the Orange application software, data analysis is implemented through workflows that are composed of widgets. The selection of widgets and the connections between them defines the data analysis workflows [9]. Orange 3.22.0 was used in this work.

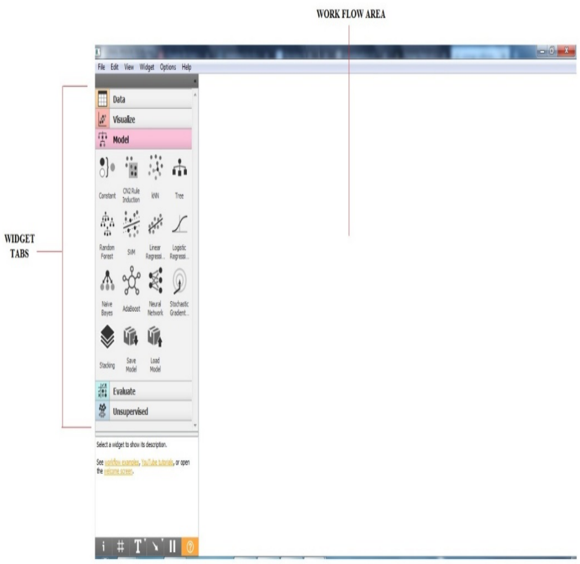

Fig. 1. Orange 3.22.0 User Interface

The Orange 3.22.0 comprises of several algorithms but only the ones applicable to this study will be discussed briefly.

2.1.1 Decision Tree

Decision Tree is a machine learning technique that uses the treelike characteristics. It is one of the most commonly used data mining methods. It uses a top-down recursive method to appraise the attribute values of nodes in the tree. Then, based on the various attribute value, the branch down from the node is determined. Two main processes are involved in the development of the decision tree algorithm. The first stage is the tree building where parts of the training data are selected and a decision tree is built, while the second stage is the pruning stage where the remaining data is used to check the generated decision tree for errors [10].

2.1.2 Random Forests

Random forest (RF) or random decision forest is an ensemble learning method categorised under the homogeneous base learner. From the name, the base learner is a decision tree, hence possesses simpler structure [11]. From the computational point of view, the Random Forest is capable of dealing with both classification and regression problems, with a high training and prediction classifier speed. It also has the ability for direct use in high dimensional problems [12]. During the training process, the out-of-bag (OOB) error approximates the RF's error [13].

2.1.3 AdaBoost

Boosting algorithm is a combination of multiple weak learners, in this case, decision trees. The working principle is, whenever a new tree model is added, the general tree is removed and only the strongest tree remains. By this process, the accumulation of iterative computations yields gradual improvement of the overall performance of the model. However, there is a challenge. Some samples of data set are classified correctly after obtaining the first basic tree model, while others are wrongly classified. But since the algorithm is based on improving weak classification ability, the data training continues until the desired result is achieved [14].

2.1.4 K-NN

The K-Nearest Neighbor (KNN) is also a very popular machine learning algorithm. It is a less complex and easily executable algorithm, yet very efficient in terms of prediction performance. In fact, its core idea is based on prediction of the label of a query sample. The KNN algorithm does not make a definite assumption of the data's distribution. This is because, as an instance-based learning algorithm that does not require any training before predicting an outcome, incremental learning is easily used. Hence, this algorithm has been effectively used in a number of supervised learning tasks including classification and regression [15].

2.1.5 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a type of machine learning technique that is based on classification. It is based on the idea of proffering solutions to large dimensional problems that are two folds in order for the classifier to rely on a few numbers of support vectors so as to attain structural risk minimisation principle. Also, SVM can be used to carry out detection of anomalies and in modern day big data, it can be applied to multidomain systems [16].

2.1.6 Artificial Neural Network (ANN)

The artificial neural network (ANN) was patterned after the human biological neural system. ANN comprises of neurons adjoined partially or completely. The neuron which is a unit that is not linear gets its signals from other units, thereby giving an output. The signals thus received by a neuron are changed by real numbers called synaptic weights. Through a process of training, these weights are modified. Consequently, ANN can then learn hidden connections from typical cases to solve specific problems in place of using a set of rules. A certain process of evaluation is undergone by the neurons: input signals are fed into the system which processes them through an activation (or transfer) function. These signals are returned to the environment through the output neurons [17-18].

ANN has been used successfully for predictions and it has been proven to be very efficient. The successful application of ANN to a number of problems including the prediction of signal strength at VHF and UHF bands abounds [19-22].

2.1.7 Linear Regression

Linear Regression is one of the most popular and simplest type of machine learning algorithm. It is used to carry out predictive analysis using regression models. A dependent variable value 'y' is predicted by a given independent variable 'x' using the linear regression model. A simple linear regression model can be expressed as [23]:

$$y = a_1 + a_2 x + e \tag{1}$$

where y is the dependent variable, x is the independent, a_1 is the intercept of the regression line on the vertical axis, a_2 is the slope of the regression line and e is the random error term.

3. METHODOLOGY

3.1 Measurement of Signal Strength

Signal strength data were measured at regular intervals for six months from the Nigerian Television Authority (NTA) transmitter, Minna at a frequency of 210.25 MHz. Geberit Digital Signal Level Meter, GE-5499 was used to take the measurement of the received signal strength. The line of sight distance between the transmitter and the receiver is 7.15 km. The Geberit signal level meter is shown in Figure 2. The measurements were taken at the Federal University of Technology, Bosso Campus, Minna.

Fig. 2. Geberit Signal Level Meter

3.2 Measurement of Atmospheric Parameters

The atmospheric parameters of temperature, pressure, relative humidity and wind speed were also measured at the Federal University of Technology, Bosso Campus, Minna (Figure 3). The instrument used for measuring these parameters is the Campbell CR-1000 data logger.

Fig. 3. Weather Station Housing the Campbell CR-1000 Data Logger

Computation in orange data mining is divided into two-step processes. These are the Learning step in which a classification model is developed and the Classification step in which the model is used to compute class labels for a given data. Classification task involves two broad approaches to learning using data mining algorithms. There are also Supervised and Unsupervised learning, the supervised learning approach is used in this paper. The various models were applied to the dataset with no omission of any data point.

The data obtained were split into two subsets of training and test data. The larger subset (training data) which contains 60% of the data instances was sent to each model via the training data input and later connected to the prediction widget so that the algorithms can produce a corresponding model that will be used for computation. The remaining 40% of the data was also sent directly to the prediction widget so that the target class (signal strength class) can be computed based on the model built by the algorithms. A data table was also connected as an output to the prediction widget so as to have the full outcome of each value predicted by the algorithms for each data point and the corresponding feature data point used for the computation. Finally, the test and score widget was used for evaluating each of the models. Figure 4 illustrates the methods used for training the models.

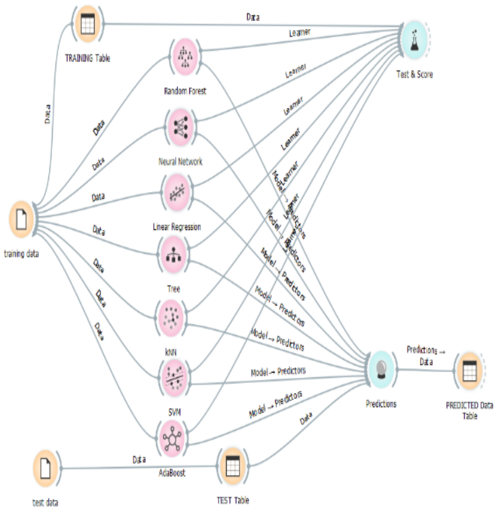

Fig. 4. Model Training for Computation

3.3 Method of Evaluation

Evaluation methods for the accuracy of each model used in this paper were based on mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE).

3.3.1 Mean absolute error (MAE)

This is a measure of the difference between two continuous variables. It is the average vertical and horizontal distance between each point and the identity line which is given by:

$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} = \frac{\sum_{i=1}^{n}|e_i|}{n} \quad (2)$$

where y_i is the prediction, x_i is the true value and $|e_i| = |y_i - x_i|$.

3.3.2 Mean square error (MSE)

The mean square error (MSE) sometimes called mean squared deviation (MSD) is a measure of how close a fitted line is to a data point. It is given as:

$$MSE = MSD = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \tilde{Y})^2 \quad (3)$$

where $(Y_i - \tilde{Y})^2$ is the squares of the errors and n is the number of samples.

3.3.3 Root mean square error (RMSE)

This is also referred to as root mean square deviation (RMSD). It is the standard deviation of the prediction errors (residuals) which is a measure of how far data points are from the regression line. It is expressed as:

$$RMSE = RMSD = \sqrt{\sum_{i=1}^{n}(Y_i - \tilde{Y})^2} \quad (4)$$

4. RESULTS AND DISCUSSION

The aforementioned models were employed as computation models to obtain the computation of signal strength. 60% of the data was used to train the model, while the remaining 40% were used as test data to determine the accuracy of the computation for all the models.

A total of 120 dataset were used in computing the signal strength. Out of these, 72 data points were used in training the models, while 48 data points were used in testing the models. The accuracy of the c`omputed signal strength obtained from all the models were then determined using the MSE, RMSE and MAE error metrics. Outliers were applied to help in finding patterns and removing data points that are not relevant to the signal computation.

Figure 5 is a graphical illustration of the test signal computation carried out for all the trained models.

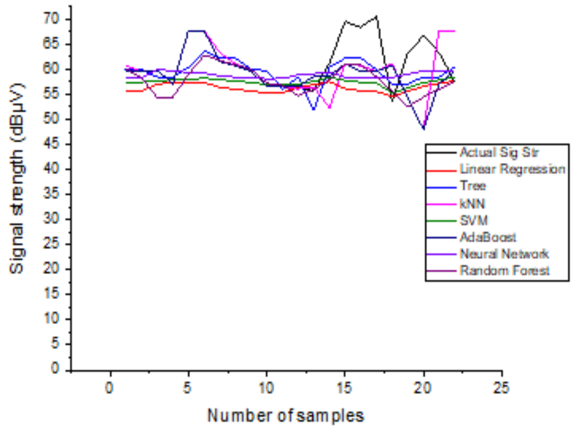

Fig. 5. Signal Strength Computation for January

Table 1 gives the performance evaluation of the models.

Table 1. Performance Evaluation of Signal Strength Computation for January

Model	Error Estimator		
	MSE	*RMSE*	*MAE*
AdaBoost	3.61	0.27	9.91
Tree	3.70	0.28	10.06
kNN	3.82	0.30	10.78
ANN	4.02	0.34	11.84
Random Forest	5.00	0.40	11.97
SVM	5.59	0.49	12.41
Linear Regression	6.20	0.74	13.26

From Figure 5, it is observed that AdaBoost model computed the signal strength accurately having the closest conformity to the actual signal strength even as the error metrics in Table 1 confirmed the graphical illustration of the signal computation for all the trained models. From Table 1, it is observed that AdaBoost has the least error values compared to the other models. The MSE and RMSE values computed for AdaBoost were 3.61 and 0.27 respectively.

To obtain this optimal computation, AdaBoost model parameters were modified. The tree base estimator was used and set to 50 estimators with a unit learning rate. SAMME.R classification algorithm was also used with linear regression loss function.

The Decision Tree model was next to AdaBoost in order of accuracy. Also, the data prediction parameters were modified to achieve this level of accuracy. The model was modified to include binary trees with 2 minimum number of instances in leaves. In addition, minimal level for subsets splitting was set at 5 with 100 maximal tree depth. Finally, the classification was set to stop at 95% majority. Next in order of accuracy was the k-Nearest Neighbor. The parameters were modified to obtain the highest level of accuracy for the model. Only 1 neighbor was used and Euclidean metric with distance set at weight.

The signal strength computation for the month of February is shown in Figure 6.

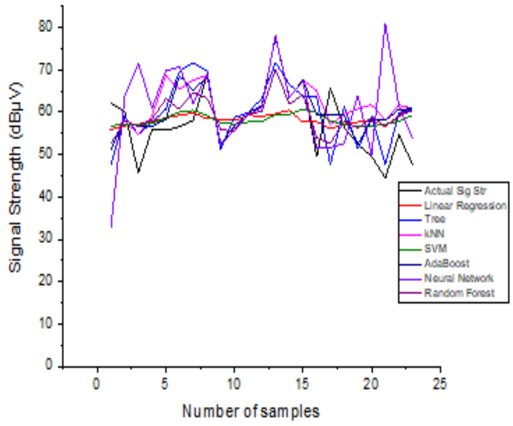

Fig. 6. Signal Strength computation for February

Table 2 gives the performance evaluation of the models.

Table 2. Performance Evaluation of Signal Strength Computation for February

Model	Error Estimator		
	MSE	*RMSE*	*MAE*
SVM	2.81	0.10	8.31
Linear Regression	2.92	0.12	9.40
Random Forest	3.21	0.14	10.50
AdaBoost	3.63	0.16	12.51
Tree	3.82	0.18	13.50
kNN	4.05	0.21	14.80
ANN	5.81	0.33	15.90

From Figure 6, it is seen that the SVM model is the most accurate as computed values were very close to the actual signal strength. It can be observed also from Table 2 that the SVM had the least error metrics from the computed signal strength values. In Comparison with other models, the MSE and RMSE values computed for the SVM are 2.81 and 0.10 respectively.

Also, in order to obtain this satisfactory computation, SVM model parameters were modified. The normal SVM was used with regression loss epsilon and cost set at 0.10 and 1.00 respectively. Polynomial kernel was also used, while the optimization parameters were set at 00010 numerical tolerance and 100 iteration limits.

The Tree model is the model next to the SVM in order of accuracy. Data prediction parameters were modified to achieve this level of accuracy, the model was modified to include binary trees with 2 minimum numbers of instances in leaves. Moreover, minimal level for subset splitting was set at 5 with 100 maximal tree depth. Finally, classification was set to stop at 95% majority. Next in order of accuracy was the k-Nearest Neighbor. The parameters were modified to obtain the highest level of computation for the model. Only 1 neighbor was used and Euclidean metric with distance set at weight.

Figure 7 shows the signal strength computation for the month of March.

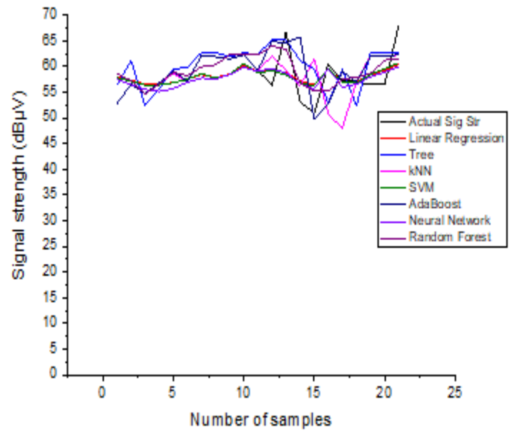

Fig. 7. Signal Strength Computation for March

Figure 7 shows that the ANN model was the most accurate method as computed values were very close to actual signal strength. Table 3 gives the performance evaluation of the models.

Table 3. Performance Evaluation of Signal Strength Computation for March

Model	Error Estimator		
	MSE	*RMSE*	*MAE*
AdaBoost	3.70	0.09	10.30
Tree	4.42	0.06	10.46
kNN	4.80	0.30	12.31
ANN	3.52	0.02	10.70
Random Forest	4.13	0.16	9.91
SVM	4.86	0.02	10.70
Linear Regression	4.63	0.08	10.34

The error metrics computed in Table 3 confirmed that the ANN model has the least error for March compared to other models. The MSE and RMSE computed for the ANN model are respectively 3.70 and 0.09.

Again, to obtain this optimal computation, the ANN model parameters were modified. The hidden layer was increased to 150 neurons and the 'tanh' activation function with the SDG regularisation was employed. The number of iterations was set to 200. The AdaBoost model was next model to the ANN model in order of accuracy. Also, data computation parameters were modified to achieve this level of accuracy. The tree base estimator was used and set to have 50 estimators with a unit learning rate. SAMME.R classification algorithm was also used with linear regression loss function. Next in order of accuracy was the Random Forest. To achieve optimum prediction for the Random Forest, the number of trees were reduced to 10, while 5 attributes were considered at each split.

Signal strength computation for the month of May is shown in Figure 8.

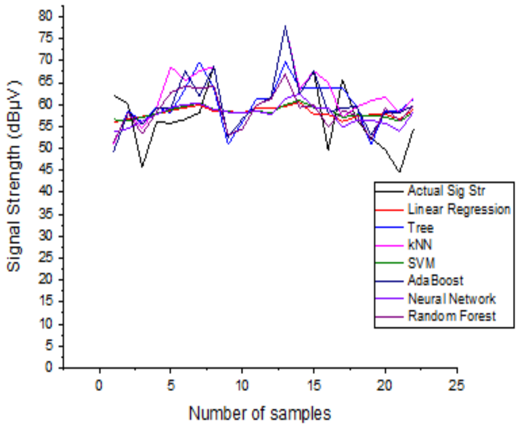

Fig. 8. Signal Strength Computation for May

Table 4 gives the performance evaluation of the models.

Table 4. Performance Evaluation of Signal Strength Computation for May

Model	Error Estimator		
	MSE	***RMSE***	***MAE***
AdaBoost	4.13	0.04	11.86
Tree	6.78	0.64	14.91
kNN	4.29	0.13	10.85
ANN	4.62	0.14	12.40
Random Forest	4.59	0.24	10.28
SVM	5.87	0.10	12.22
Linear Regression	5.86	0.14	12.40

From Figure 8, it is seen that the AdaBoost model is the most accurate method as predicted values were very close to the actual signal strength. The errors computed in Table 4 confirmed this result as the model has the lowest MSE and RMSE with values of 4.13 and 0.04 respectively.

To obtain this best computation, the tree base estimator was used and set to have 50 estimators with a unit learning rate. SAMME.R classification algorithm was also used with linear regression loss function. The k-Nearest Neighbor model is the model next to AdaBoost in order of accuracy. Also, data prediction parameters were modified to achieve this level of accuracy. The Chebyshev metric with one neighbor were used to modify the k-Nearest Neighbor model. Next in order of accuracy is the Random Forest and to achieve this optimal computation, the number of trees were reduced to 10, while 5 attributes were considered at each split.

Figure 9 shows the illustration of the signal computation for the month of June.

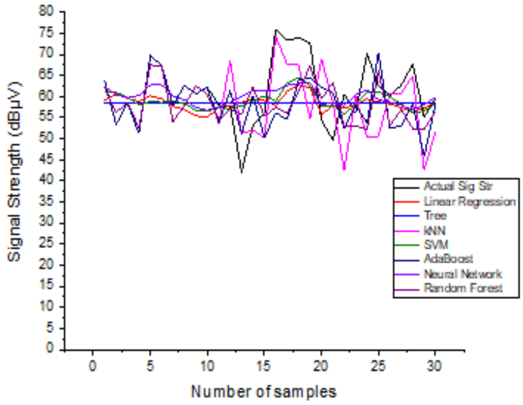

Fig. 9. Signal Strength Computation for June

From Figure 9, it is observed that AdaBoost model is the most accurate method as predicted values were close to the actual signal strength. Table 5 gives the performance evaluation of the models.

Table 5. Performance Evaluation of Signal Strength Computation for June

Model	Error Estimator		
	MSE	***RMSE***	***MAE***
AdaBoost	3.76	0.33	9.39
Tree	4.81	0.13	10.66
kNN	4.67	0.02	11.31
ANN	3.91	0.01	9.83
Random Forest	5.00	0.19	10.30
SVM	5.31	0.31	12.74
Linear Regression	5.18	0.28	11.81

It can be observed from Table 5 that AdaBoost has the least error metric from the computed signal strength values. In comparison with other models, the error values computed for AdaBoost is 3.76 and 0.33 for the MSE and the RMSE respectively.

To obtain this satisfactory computation, the tree base estimator was used and set to have 50 estimators with a unit learning rate. SAMME.R classification algorithm was also used with linear regression loss function. The ANN is the model next to AdaBoost in order of accuracy. The hidden layer was increased to 150 neurons. The ‘ReLu’ activation function and SDG regularisation was also employed. The number of iterations was set to 200. Next in order of accuracy was the k-Nearest Neighbor and to achieve an optimal computation, the Euclidean metric with one neighbor was used to modify the kNN model.

The signal strength computation for the month of July is given in Figure 10.

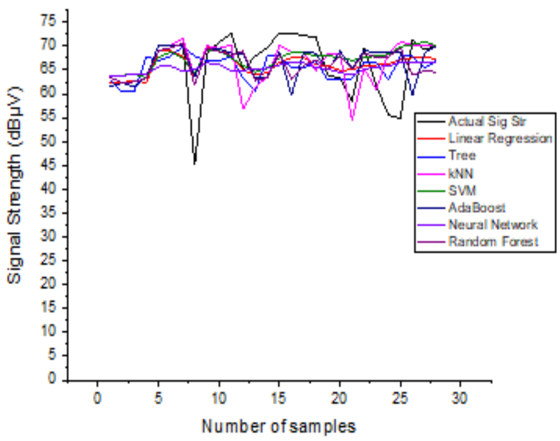

Fig. 10. Signal Strength Computation for July

From Figure 10, it is observed that the ANN model computed the signal strength accurately, having the closest conformity to the actual signal strength. Table 6 gives the performance evaluation of the models.

Table 6. Performance Evaluation of Signal Strength Computation for July

Model	Error Estimator		
	MSE	*RMSE*	*MAE*
AdaBoost	5.17	0.01	12.44
Tree	5.71	0.08	12.96
kNN	4.80	0.09	11.68
ANN	4.43	0.44	9.36
Random Forest	5.17	0.12	11.74
SVM	5.08	0.13	11.68
Linear Regression	4.54	0.25	10.82

From Table 6, it is observed that the ANN had the least mean square error output compared to the other models. MSE and RMSE values computed for the ANN are 4.43 and 0.44 respectively.

In order to obtain this good performance, the ANN model parameters were modified. The hidden layer was increased to 150 neurons and the 'tanh' activation function and SDG regularisation was also employed and the number of iterations was set to 100. The Linear Regression model is the model next to the ANN in order of accuracy. Also, to achieve this level of accuracy for the linear regression model, the regression function was modified without regularization.

5. CONCLUSION

Signal strength computation was achieved in this paper without introducing complex and long-lasting mathematical equations. This study utilised Seven (7) different machine learning models. These are the Random Forest, Artificial Neural Network, Linear Regression, Decision Tree, k-Nearest Neighbor, Support Vector Machine and AdaBoost. In order to obtain optimum computations of VHF signal strength, individual model modification techniques that would give the highest computational accuracy was studied and applied. This therefore, provided a simple and very efficient way of obtaining satisfactory signal strength computations in the VHF link. It was observed that the accuracy of the computation was greatly influenced by the amount of training data which was used in training the models. The results obtained showed that the AdaBoost model was the overall most accurate model. This was followed by the ANN model. It was also observed that the error margin of computation was very low, hence indicating that the models can be effectively relied on for computation of signal strength. In view of the foregoing findings, it is therefore recommended that the application of these models in the computation/prediction of other forms of signals or wave communication be further applied. Also, the utilisation of these models in other fields of data analysis that require forecasting should be encouraged. In addition, further studies should be carried out on the optimisation of model parameters to enhance higher accuracy of computation.

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REFERENCES

[1] B. F. Margarita, "DSD variation on rain rate estimate algorithms of X-band polarimetric and radar and rainfall characterization in tropical environments using 2DVD, rain gauges and TRMM data," MSc. thesis, University of Puerto Rico, 2005.

[2] M. V. S. N. Prasad, R. T. Rao, I. Ahmad, and K. M. Paul, "Investigation of VHF signals in bands I and II in southern India and model comparisons," Indian Journal of Radio and Space Physics, vol. 35, 2006, pp. 198-205.

[3] K. C. Igwe, O. D. Oyedum, M. O. Ajewole and A. M. Aibinu, "Measurements of VHF Signal Strength for Terrestrial Broadcast Service in Minna, North Central Nigeria," Journal of Science, Technology, Mathematics and Education (JOSTMED), vol. 13(2), 2017, pp. 63-71.

[4] K. C. Igwe, "Characteristics of VHF line-of-sight propagation for point-to-area network in a tropical atmosphere," Journal of Science and Technology, vol. 14(2), 2022, pp. 8-19.

[5] J. D. Parsons, "The mobile radio propagation channel," 2nd edition, John Wiley & Sons Ltd., 2000, pp. 15-127.

[6] N. T. Surajudeen-bakinde, N. Faruk, M. Salman and S. Popoola, "On Adaptive Neuro-Fuzzy Model for Path Loss Prediction in the VHF Band," ITU Journal: ICT Discoveries, vol.1, 2018, pp. 1-9.

[7] D. W. Kifle, L. C. Gimenez, B. Wegmann, I. Viering and A. Klein, "Comparison and extension of existing 3D propagation models with real-world effects based on ray-tracing," Wireless Personal Communications, vol. 78(3), 2014, pp. 1719-1738.

[8] J. Demsar and B. Zupan, "Orange : Data mining fruitful and fun - A historical perspective," Informatica, vol. 37, 2013, pp. 55-60.

[9] P. Godec, N. Ileni, Č. Andrej, M. Stra, A. Erjavec, A. Pretnar, J. Dem, M. Toplak, Ž. Lan, J. Hartman, H. Wang, R. Bellazzi, S. Garagna, M. Zuccotti, D. Park, G. Shaulsky and B. Zupan, "Democratized image analytics by visual programming through integration of deep models and small-scale machine learning, Nature Communications, 2019, pp. 1-8.

[10] Z. Zhang, Z. Zhao and D. Yeom, "Decision Tree Algorithm-Based Model and Computer Simulation for Evaluating the Effectiveness of Physical Education in Universities" Wiley Hindawi, 2020, pp. 1-11.

[11] C. Zhang and Y. Ma, "Ensemble Machine Learning: Methods and Applications," Springer, New York, NY, USA, 2012.

[12] A. Galicia, R. Talavera-Llames, A. Troncoso, I. Koprinska and F. Mart´ınez-Alvarez, “Multi-step forecasting for big data time series based on ensemble learning,” Knowledge-Based Systems, vol. 163, 2019, pp. 830-841.

[13] M. Schonlau, and R. Y. Zou, “The random forest algorithm for statistical learning,” The Stata Journal, vol. 20(1), 2020, pp. 3-29.

[14] C. Wang, S. Xu, and J. Yang, “Adaboost Algorithm in Artificial Intelligence for Optimizing the IRI Prediction Accuracy of Asphalt Concrete Pavement,” Sensors, vol. 21(5682), 2021, pp. 1-16.

[15] S. Kang, “k -Nearest Neighbor Learning with Graph Neural Networks,” Mathematics, vol. 9(830), 2021, pp. 1-12.

[16] B. Gaye, D. Zhang, and A. Wulamu, “Improvement of Support Vector Machine Algorithm in Big Data Background,” Hindawi (Mathematical Problems in Engineering), 2021, pp. 1-9.

[17] J. C. F. Pujol, J. M. A. Pinto, “A neural network approach to fatigue life prediction,” Int. J. of Fatigue, vol. 33, 2011, pp. 313-322.

[18] J. Schmidhuber, “Deep learning in neural networks: An overview,” Neural Networks, vol. 61, 2015, pp. 85-117.

[19] B. J. Cavalcanti, G. A. Cavalcante, “A hybrid path loss prediction model based on artificial neural networks using empirical models for LTE and LTE-A at 800 MHz and 2600 MHz,” J. of Microw., Optoelectronics and Electromagmagnetic Applications, vol. 16(3), 2017, pp. 708-722.

[20] K. C. Igwe, O. D. Oyedum, M. O. Ajewole and A. M. Aibinu, “Received signal strength computation for broadcast services using artificial neural network,” IEEE 13th Int. Conf. on Electronics, Computer and Computation, 2017, pp. 1-6.

[21] S. I. Popoola, E. Adetiba, A. A. Atayero, N. Faruk, C. T. Calafate, “Optimal model for path loss predictions using feed-forward neural networks,” Cogent Engineering, vol. 5, 2018, pp. 1-19.

[22] K. C. Igwe, O. D. Oyedum, A. M. Aibinu, M. O. Ajewole and A. S. Moses, “Application of artificial neural network modeling techniques to signal strength computation,” Heliyon, vol. 7(3), 2021, pp. 1-9.

[23] R. Shen, and B. Zhang, “The research of regression model in machine learning field,” MATEC Web of Conferences, vol. 176, 2018, pp. 1-4.