

ON ADAPTIVE NEURO-FUZZY MODEL FOR PATH LOSS PREDICTION IN THE VHF BAND

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Abstract – Path loss prediction models are essential in the planning of wireless systems, particularly in built-up environments. However, the efficacies of the empirical models depend on the local ambient characteristics of the propagation environments. This paper introduces artificial intelligence in path loss prediction in the VHF band by proposing an adaptive neuro-fuzzy (NF) model. The model uses five-layer optimized NF network based on back propagation gradient descent algorithm and least square errors estimate. Electromagnetic field strengths from the transmitter of the NTA Ilorin, which operates at a frequency of 203.25 MHz, were measured along four routes. The prediction results of the proposed model were compared to those obtained via the widely used empirical models. The performances of the models were evaluated using the Root Mean Square Error (RMSE), Spread Corrected RMSE (SC-RMSE), Mean Error (ME), and Standard Deviation Error (SDE), relative to the measured data. Across all the routes covered in this study, the proposed NF model produced the lowest RMSE and ME, while the SDE and the SC-RMSE were dependent on the terrain and clutter covers of the routes. Thus, the efficacy of the adaptive NF model was validated and can be used for effective coverage and interference planning

Keywords – COST 231, generalized bell, Hata, neuro-fuzzy, path loss

1. INTRODUCTION

Predicting the propagation of electromagnetic waves is of great significance in the design and planning of wireless communication systems. Propagation models are essential in evaluating the performance of a wireless system and quality of the received signal. Empirical path loss models have been found to be the widely used models due to their simplicity and ease of use, as the implementation of the models do not require much computational efforts, and, are less responsive to the physical and geometrical structures of the environments [1]. These make them attractive, although a major drawback of utilizing these models is the lack of accuracy, especially when deployed in another environment other than the one where the measurement was taken. For example in [2-5], several of these models were tested in a typical urban and rural Nigerian terrain and they were found to be inconsistent in prediction, and have high prediction errors. Although, in [6-8], some of the most performing models, were tuned to minimize errors and improve prediction accuracy. Yet the tuned models were found to be site-specific. On the other hand, the deterministic

models seem to have better prediction accuracy because of the availability of detailed information about the propagation environment. However, they are computationally intensive and time consuming [9]. Moreover, despite the inclusion of site-specific information, the deterministic models do not always provide more accurate predictions than the empirical models [9-10]. This therefore raises more questions to which model(s) can provide optimum prediction with minimal complexity, as such, the need to incorporate artificial intelligence (AI) and heuristic algorithms to improve path loss prediction. Different AI techniques have been adopted, as evident in the literature, for path loss prediction. Tamma *et al* [11] developed an artificial neural network (ANN) model for path loss prediction in the UHF (ultra-high frequency) band based on the measurement data collected in Tripoli, Turkey. The accuracy of the proposed model was evaluated and compared to that of the Hata model and it was found that the ANN model provided more accurate prediction. In [12], an adaptive network based fuzzy inference system (ANFIS) was used to predict path loss in the urban settlement of the Habiye region of Istanbul in the 900 MHz band. The ANFIS model

increased the prediction accuracy by 15% relative to the Bertoni-Walfisch model. Joel and Elmer in [13] conducted a comparative analysis of the neural network (NN), free space loss (FSL), and Egli models. The NN model was most efficient for path loss prediction in digital TV macro-cells in the UHF band. Achieving the lowest prediction error using the AI models was not the only benefit over the empirical path loss propagation models as Ozdemir *et al* [14] showed that the ANN model performed better than the theoretical and the empirical propagation models in terms of prediction accuracy, less complexity and time. Furthermore, the authors proved that within the ANN model, the model that employed the Levenberg-Marquardt learning algorithm had minimal prediction error compared to the one that used Epstein-Peterson. In [15] the performance of ANFIS for optimal power control for cognitive radio spectrum distribution was investigated. ANFIS produced the lowest prediction error and was recommended as the most suitable method for power scale control. Vishal and Sharma [16] employed a fuzzy logic (FL) model to predict path loss as a function of path loss exponent in the fringe areas of a suburban region of Clementtown and Dehradun in India. It is worth mentioning that some efforts have also been made to compare the performance of some AI models used in path loss prediction. For instance, Vahala *et al.*, [17] investigated the electromagnetic interference pattern caused by portable devices onboard Airbus 319 and 320 with respect to various receivers on the aircraft using NF modelling (NFM). The results obtained were compared to the ANN model and it was found that the NFM performed better.

Although application of heuristic algorithms for path loss prediction in an urban macro-cellular environment [18-21] is gaining momentum, most of the works that focus on investigating the suitability of adaptive NF technique for path loss prediction in the VHF band are very limited. Moreover, due to the peculiar nature of our terrain environment and the wide deployments of wireless systems operating on the VHF bands, there is a need to test the efficacy of the NF model. Therefore, this paper introduces an adaptive neuro-fuzzy (NF) approach to path loss prediction in the VHF band within the Nigerian propagation terrain context. The predictions of the NF model were compared to those of the widely used empirical models such as Hata, COST 231, Egli and ECC-33 models. The performances of the models under investigation were evaluated using the Root Mean Square Error (RMSE), Spread Corrected RMSE (SC-RMSE), Mean Error (ME), and Standard Deviation (SD), relative to the measured data.

2. METHODOLOGY

This section is divided into two parts: the first part describes the measurement procedure and the second part explains the adaptive NF approach to path loss modelling in the VHF band.

2.1. Measurement Campaign Procedure

Measurements were carried out in Ilorin, Kwara State, Nigeria (Long 4°36'25"E, Lat 8°25'55"N). The received signal power was measured from the NTA Ilorin transmitter which operates on VHF band at a frequency of 203.25 MHz. For the receiver, a dedicated Agilent spectrum analyzer, N9342C, was used and this was properly positioned in a vehicle and driven at an average speed of 40 km/hr to minimize Doppler effects. The analyzer has a displayed average noise level (DANL) of -164 dBm/Hz and can detect even very weak signals. A whip retractable antenna (70 MHz – 1 GHz), a global positioning system (GPS) receiver and a dedicated memory stick for data storage were coupled to the analyzer. The external GPS receiver was attached to the roof of the vehicle, while the spectrum analyzer was positioned inside the vehicle. The four measurement routes visited are: Murtala Mohammed way, Old Jebba road, Pipeline road, and Ogbomoso road. These routes are characterized with complex terrain propagation features with the presence of hills, valleys and urban clutters. The terrain elevation varies between 350 m to 403.7 m. The routes i.e. MURTALA, PIPELINE, OLD JEBBA AND OGBOMOSO are dual carriage, single lane road, two-lane road and two-lane respectively. The MURALA route is considered the busiest among the routes. The average buildings along these routes are two storeys. The total length of the routes and total number of data points were 75.5 km and 92,280 respectively. The received signal strength data were filtered to minimize noise and preserve the shadowing effects. This reduced the number of data sets per route to 500.

2.2. Prediction Model

NF modelling is a kind of fuzzy inference system which prepares the mapping of inputs to outputs. It consists of both FL and ANN in the development of mapping the inputs to the output [15]. It consists of five layers as shown in Fig. 1. The nodes in these layers are either fixed or adaptive. The adaptive nodes are symbolized by the square shapes, while the fixed nodes are represented by the circular shapes. To describe the structure, a first order Sugeno model has been used because the output is a crisp value that does not require defuzzification. A Sugeno based NF has a rule of the form [15]:

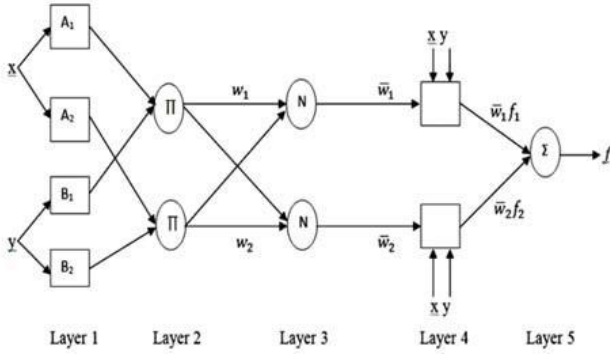


Fig. 1. Neuro-fuzzy structure

Rule 1:

If x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + r_1$ (1)

Rule 2:

If x is A_2 and y is B_2 then $f_2 = p_2x + q_2y + r_2$ (2)

Layer 1: A node in this layer is adaptable and is given as:

$$L_j^1 = \mu A_i(x) \quad i = 1, 2 \quad (3)$$

x is the input to i th node, A_i is the alterable language related to this node and the membership function of A_i is $\mu A_i(x)$ and normally taken as:

$$\mu A_i(x) = \frac{1}{1 + [(\frac{x-f_i}{d_i})^2]^{e_i}} \quad (4)$$

$\{d_i, e_i, f_i\}$ is the antecedent parameters set. Eqn. (4) represents the generalized bell membership function (MF) which was chosen for this work because it produced the best accuracy when compared to the other membership functions.

Layer 2: This layer comprises of fixed nodes and it solves the firing power w_i of a rule. The multiplication of the incoming signals is the output of each node and is given by:

$$L_i^2 = w_i = \mu A_i(x) \times \mu B_i(y), i = 1, 2 \quad (5)$$

$\{p, q \text{ and } r\}$ is the consequent parameters set which are established by the least squares method.

Layer 3: Each node is constant in this layer with the output given by

$$L_i^3 = w_i = \frac{w_i}{\sum w_i}, i = 1, 2 \quad (6)$$

Layer 4: The adaptable output of this layer is given by

$$L_i^4 = w_i f_i = w_i(p_i x + q_i y + r_i), i = 1, 2 \quad (7)$$

Layer 5: The output of this layer is the summation of all incoming signals and is given by

$$L_i^5 = \sum_{i=1}^2 w_i f_i = \frac{\sum w_i f_i}{\sum w_i} \quad (8)$$

The optimization method used for training the network in this work is the hybrid method which combines both the back propagation gradient descent algorithm and the least square errors estimate used to establish the input and output parameters respectively. The output parameters are adjusted first using the least squares algorithm and those of input parameters by back propagating the faults from the output using the gradient descent method until the training is completed.

3. RESULTS AND DISCUSSION

Figs. 2 to 5 show the graphical depiction of the measured and predicted path losses as a function of distance for each of the four routes considered. It is worth pointing out that from the figures, the prediction by the NF model in all the four routes performed the best among all the considered models as it mimicked the measured data. In Fig 2, the variation of path loss with distance for MURITALA along the route and the predictions of the four empirical models were superimposed on the measured loss. The Egli, COST 231 and Hata models under-predicted the path loss throughout the measurement route, except within 3-4.5 km where the Hata model provided good fitness. The ECC-33 model generally fluctuated between over and under-prediction of the path losses with respect to the measured path losses. Along this route, it can be concluded that the Egli model has the worst prediction with a mean error of -34.5 dB when compared to -1.27 dB for the ECC-33 model and $-6.52E-07$ dB for the neuro-fuzzy model. The mean error for the NF model is insignificant and this result indicated the good fitness of the model along this route.

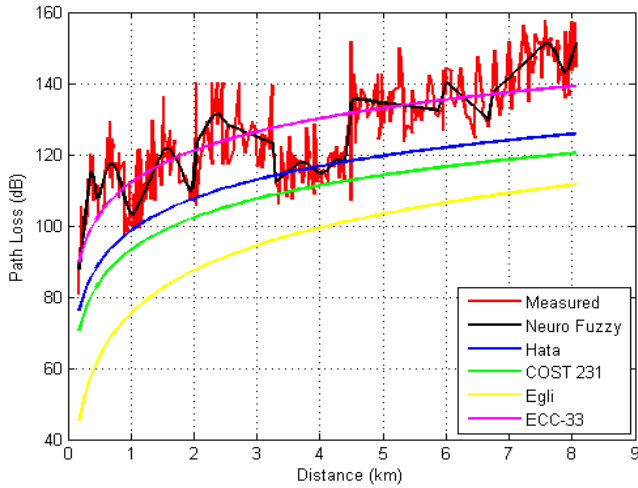


Fig. 2. Comparison of NF model path loss with measured path loss and other empirical models path loss for the MURTALA route

Fig. 3 depicts the result for the PIPELINE route. Again, the ECC-33 model gave optimum prediction up to 3 km; thereafter, it overestimated the path losses while the Hata model provided good fitness at distances above 3 km. Other models underestimated the path losses throughout the measurement distances. In Figures 4 and 5, the ECC-33 model provided good fitness, while all other empirical models underestimated the losses with various offset values.

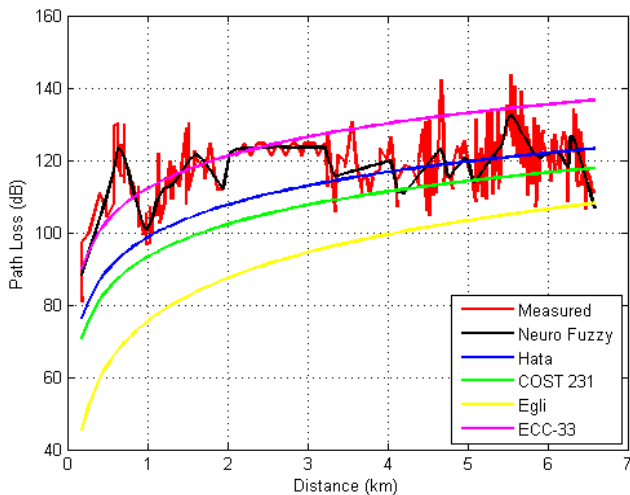


Fig.3. Comparison of NF model path loss with measured path loss and other empirical models path loss for the PIPELINE route

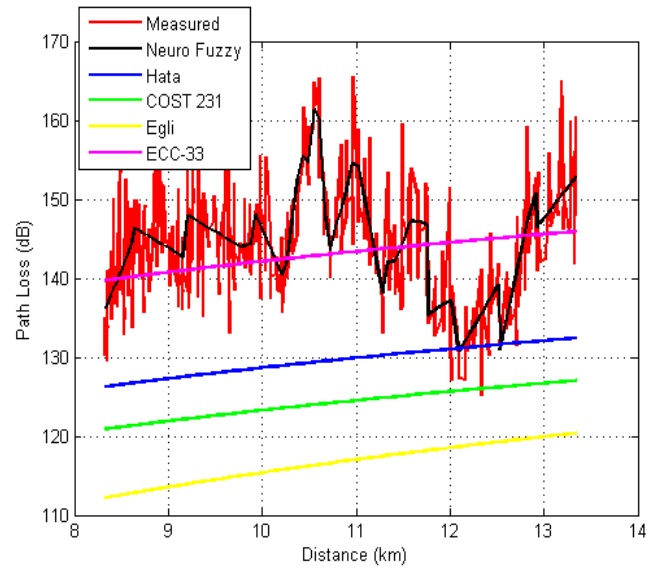


Fig. 4. Comparison of NF model path loss with measured path loss and other empirical models path loss for the OLD JEBBA route

From the figures, it was observed that the NF model provided better prediction as it followed the measured losses. In Table 1, the statistical analysis of the errors for each model across all the routes is provided. Table 1 shows how each of the models performed in terms of their RMSE, SC-RMSE, ME and SDE. RMSE between 0-7 dB is considered acceptable for urban areas [21], although for typical suburban and rural areas up to 10-15 dB [22] can still be acceptable.

For the RMSE and ME, the NF model is the lowest in average across all the routes with 5.2 dB, and -0.00000388 dB respectively, which proved to be the fittest among all the models. These values fell within the acceptable range for urban environments and as such the model did not either underestimate or overestimate the losses as the ME was found to be insignificant. The ECC-33 model gave the least values when compared to other empirical models. The average RMSE and ME were 9.48 dB and 2.27 dB respectively, although the RMSE was found to be a bit higher than the threshold limit for urban environments and the ME clearly indicated that the model underestimated the losses. Surprisingly, this model was developed to suit fixed wireless systems and recommended for European cities but is found to provide optimum predictions when compared to other contending empirical path loss propagation models.

Table 1. Performance metrics for the measurement routes

MODEL		ROUTES				
		OGBOMOSO	MURTALA	PIPELINE	OLD JEBBA	AVERAGE
NF	RMSE (dB)	5.0377	5.3232	5.5736	4.6727	5.1518
	SC-RMSE (dB)	5.8071	11.3713	4.5005	3.6978	6.3442
	ME (dB)	-4.88E-06	-6.52E-07	-3.33E-06	-6.65E-06	-3.88E-06
	SDE (dB)	8.6174	14.7883	7.3182	5.7409	9.1162
COST 231	RMSE (dB)	17.6246	22.0911	13.4102	21.6572	18.696
	SC-RMSE (dB)	11.8382	11.2586	8.0229	19.7363	12.7140
	ME (dB)	-15.8773	-20.1378	-9.9811	-20.4191	-16.6038
	SDE (dB)	6.7797	13.3675	9.2027	2.0496	7.8499
HATA	RMSE (dB)	12.985	17.3235	10.0662	16.6762	14.264
	SC-RMSE (dB)	8.138	8.592	6.2476	14.8439	9.4554
	ME (dB)	-10.4914	-14.752	-4.5952	-15.0332	-11.2180
	SDE (dB)	6.7797	13.3675	9.2027	2.0496	7.8499
EGLI	RMSE (dB)	21.8275	36.0905	24.4704	29.1706	27.890
	SC-RMSE (dB)	13.8329	19.7112	14.5071	26.5375	18.6472
	ME (dB)	-20.2792	-34.5799	-21.9709	-28.2467	-26.2692
	SDE (dB)	9.0246	17.7937	12.2498	2.7283	10.4491
ECC-33	RMSE (dB)	8.2447	9.1536	12.5833	7.3857	9.487
	SC-RMSE (dB)	5.0961	7.8597	7.0676	5.9038	6.4818
	ME (dB)	3.0725	-1.273	8.8542	-1.5622	2.2729
	SDE (dB)	6.8434	13.3076	9.1691	2.0619	7.8455

Despite the fact that the system parameters, such as the operating frequency, height of the transmitter and distance of the measurement routes fell within the validity of the Hata, COST 231 and Egli models, the models performed woefully, with an RMSE and ME of 14.26 dB, and -11.21 dB, 18.69 dB and -16.60 dB, and 27.89 dB and -26.26 dB respectively. The average standard deviation error (SDE) for the NF model is 9.11 dB, while, 7.84 dB, 7.84 dB, 10.44 dB and 7.84 dB for COST 231, Hata, Egli and ECC-33 models respectively. However, the excellent performance of the NF in terms of the mean prediction error and RMSE may not be over-emphasized as the route specific SDEs were 8.61 dB, 14.78 dB, 7.31 dB and 5.74 dB for OGBOMOSO, MURTALA, PIPELINE and OLD JEBBA routes. These are quite high and this is because the model mimicked the measured data and the deviations are noticeable along each route with varying degree of clutter effects. Furthermore, in terms of SC-RMSE, no significant impacts were observed for the NF model when compared to RMSE, apart from the MURTALA route. Ordinarily, SC-RMSE negates the impact of dispersion from the overall errors attributed

to a noisy link. For other models, the SC-RMSE was very significant as their respective mean prediction errors were quite high. The prediction errors as a function of radial distance from the transmitter for each route were equally investigated and the results are presented in Figures 6 to 9.

In Fig. 6, it was observed that the shadowing effects on the PE for the NF model along the MURTALA route, as the PE undulated along the 0 dB baseline with a varying degree of impact due to different clutter types along the route. Other models also undulated but with high amplitudes of PE with varying offsets. Interestingly, all the empirical models tend to have high prediction errors between the 0-1 km distance and which is due to their initial offset values for the models. Between 3-4.5 km, the PEs of COST 231 and Hata models were close to the 0 dB baseline, this conformed to the earlier findings reported in Fig 2. The ECC-33 model provided the least errors when compared to other empirical models but with a high prediction error within 3 and 4.5 km.

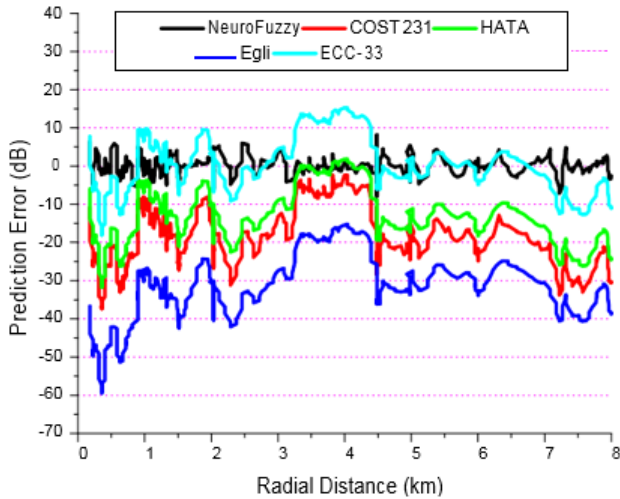


Fig. 6. Comparison of NF model prediction errors with other empirical models prediction errors for the MURTALA route

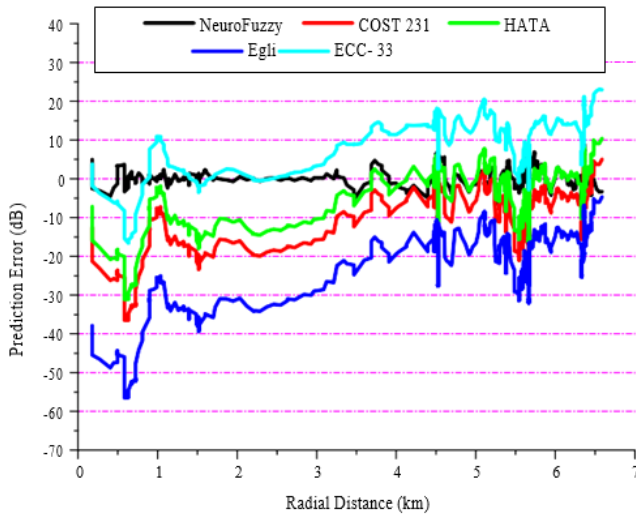


Fig. 7. Comparison of NF model prediction errors with other empirical models prediction errors for the PIPELINE route

In Fig. 7 it was shown that the NF model provided the least PE along the route. However, the ECC-33 model tried to emulate the NF model aside the initial spike between 0-1 km and $d > 3$ km, while all other models converged towards the 0 dB baseline afterwards. The situation in Figs 8 and 9 were quite different, as severe clutter effects on the PE were noticeable with several spikes along the routes.

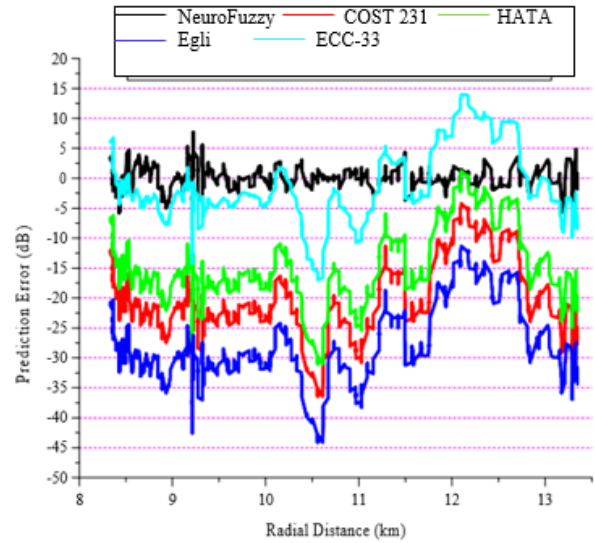


Fig. 8. Comparison of NF model prediction errors with other empirical models prediction errors for the OLD JEBBA route

Generally, the NF model can be said to have the best PE in all the routes among the considered models as it wavered close to the 0 dB line between over and under-prediction in a uniform manner throughout the distances. The result obtained in Fig. 9, for the OGBOMOSO route showed that the PEs for the Egli and COST 231 are almost similar. They largely under-predicted and showed slight over-predictions between 20-25 km and 30-35 km. The NF and the ECC-33 models' predictions are similar as well.

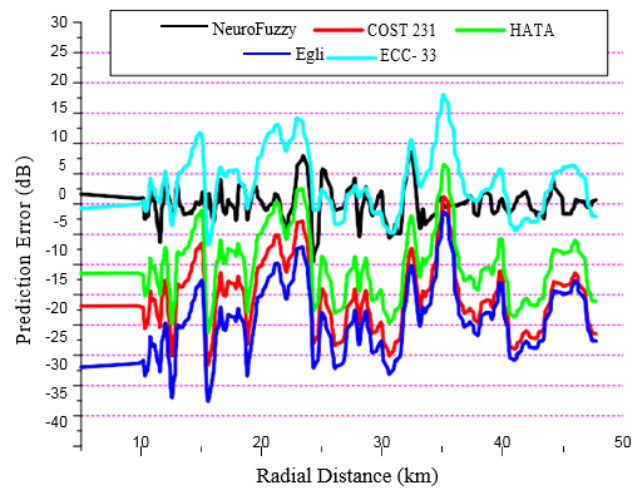


Fig. 9. Comparison of NF model prediction errors with other empirical models prediction errors for the OGBOMOSO route

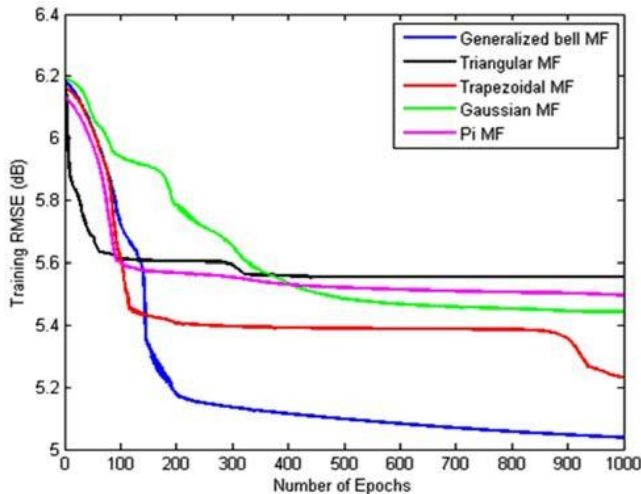


Fig. 10. Effects of membership functions types and the number of epochs on the training RMSE for the OGBOMOSO route

In Fig. 10, the impact of membership function types and epochs size on the RMSE were investigated, and these were done to establish which of the membership function types provided stability and attained fast convergence at the minimum number of epochs (number of iterations). For this exercise the OGBOMOSO route was used. Generally, the figure showed that an increase in the number of epochs for the different types of membership functions translated to a decrease in the RMSE. However, the increment in the number of epochs got to a point where the antecedent and consequent parameter sets could no longer be updated or the updates were infinitesimal and negligible, and therefore attained a steady state output for the RMSE. Also, it could be seen that the generalized bell membership function produced the lowest RMSE among the membership functions considered for this route.

4. CONCLUSION

This work is centered on the incorporation of artificial intelligence in path loss prediction. A neuro-fuzzy model was developed and used to predict path losses in the VHF band. The path loss predictions as well as the prediction errors of the proposed model were compared to that of four widely used empirical models. The proposed NF model provides the lowest errors with an average RMSE and ME of 5.2 dB and -0.00000388 dB respectively, across all the routes. The ECC-33 model gave the least values when compared to other empirical models. The average RMSE and ME were 9.48 dB and 2.27 dB respectively, although the RMSE was found to be a bit higher than the threshold limit for urban areas and the ME clearly indicated the model overestimated the losses. The work showed that the Hata, COST 231

and Egli models performed woefully, with higher errors despite the fact that the system parameters such as the operating frequency, height of the transmitter and distance of the measurement routes fell within the validity of the models. Furthermore, the paper showed that route-specific SDEs of the proposed model are quite high, as the model mimicked the measured data and the clutter effects were noticeable along each route with varying degrees. It was also discovered that the SC-RMSE had no significant impact on the NF model when compared to the RMSE. For other models, the SC-RMSE was very significant as their respective mean prediction errors were quite high. The paper also showed that an increase in the number of epochs for the different types of membership functions translated to a decrease in the RMSE and the generalized bell membership function produced the lowest RMSE among the membership functions considered for this route. In conclusion, the NF model proved to be the fittest for path loss prediction among the other models for this work. However, future work can be extended to other frequency bands, more routes with respect to the same transmitter and other transmitters, consideration of more path loss models and extension to other geographical areas.

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