Performance Comparison of Non-Linear Median Filter Built on MLP-ANN and Conventional MLP-ANN: Using Improved Dataset Training in Micro-Cell Environment

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Abstract**—**This research work explores the Levenberg-Marquardt training algorithm used for Artificial Neural Network (ANN) optimization during training and the Bayesian Regularization algorithm for the enhanced generalized trained network in training a designed non-linear vector median filter built on Multi-Layer Perceptron (MLP) ANN called model-1 and a conventional MLP ANN called model-2. The model-1 employed in the design helps in dataset de-noising to ensure the removal of unwanted signals for the improved training dataset. An early stopping method in the ratio of 80:10:10 for training, testing, and validation to overcome the problem of over-fitting during network training was employed. First-order statistical indices, the standard deviation, root mean squared error, mean absolute error, and correlation coefficient were adopted for network training analysis and comparative analysis of the designed model-1 and model-2, respectively. Two locations, Line-of-sight (location-1) and non-Line-of-Sight (location-2), were considered where the dataset was captured. The training results from the two locations for the two models demonstrated improved prediction of signal power loss using model-1 in comparison to model-2. For instance, the correlation coefficient, which shows the strength of the predicted value to the measured values (closer to 1) establishing a strong connection, gives 0.990 and 0.995 using model-1 for location-1, training with Lavenberg-Marquardt and Bayesian Regularization algorithm, respectively and 0.965 and 0.980 for model-2 using the same algorithms. It is seen that the Bayesian regularization algorithm, which optimizes the network in accordance with the Levenberg-Marquardt algorithm, gave better prediction results. The same sequence of improved perditions using designed model-1 in comparison to model-2 were seen with training results in location-2 while also adopting other employed 1st order statistical indices.

Index Terms**—**Non-linear vector median filter, Noise de-noising, Multi-layer perceptron, Artificial neural network, Levenberg-Marquardt algorithm, Bayesian Regularization algorithm.

I. Introduction

There is a need for thorough analysis of the radio signal characteristics in the propagation environment for efficient wireless communication network planning and deployment [1], [2]. The direction and magnitude of electromagnetic signal in practical wireless channel are majorly random and extremely unpredictable [2]. An excellent understanding of the phenomenon of the propagation environment and the required signal power loss prediction technique guarantees high data rate transmission and good Quality of Service (QoS) in radio access networks. The effectiveness of wireless signal is dependent on the physical constituents of the propagation environment. Mountains, foliage, buildings, and other physical structures, facilities and objects mostly obstruct direct Line-of-Sight (LOS) of radio signal propagation [3]. Diffraction, refraction, reflection, multi-path, etc. affect the propagation mechanism [2]. The electromagnetic signal propagation is also greatly influenced by the atmospheric environmental conditions of the propagation scenario [4].

A scenario where there are changes in the magnitude of the received signal strength within a short duration while the distance is relatively unchanged is said to be of small-scale and known as path loss, while in large-scale fading, there is a significant reduction in the mean received signal strength at an increased distance [5]. Radio engineering depend on different path loss models to carry out interference feasibility studies, obtain efficient radio signal coverage estimation, make adequate frequency allocation, determine optimal base station location, and select the adequate antennas. Conventionally, each of the path loss models is either empirical, semi-empirical, or deterministic model. The effectiveness of these models has been tested in diverse environments and across various bands, in some cases, some of the models were tuned for improved predictions accuracy [6].

Jha and Jain [7] have presented a model for electromagnetic field strength measurement at *917.5 MHz* forest terrain for device-to-device communications. Comparison of the measured loss with some of the empirical path loss models were carried out. The dominant propagation path loss, which was through the foliage, resulted in high loss levels and it was obtained that at a distance more than 1000 m, the measured signal strength is in line with the fourth power law. Single slope path loss models were seen to show deficiencies in the accurate capturing of the effect of physical environments by *Benmus et. al.* [8], while the performance of multi-slope path loss models were studied and compared using

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different path loss models. Optimized path loss models to improve accuracy in path loss propagation for in outdoor environments were studied by *Khan et. al.* [9].

The individual collective findings from past research work show inconsistency in the performance of the existing traditional models with high prediction errors, thus important to explore improved methods of prediction of path loss using path loss models with high efficiency and accuracy [10], [11]. Artificial Neural Network (ANN) models have proved to be an improved method for path loss prediction with high efficiency and accuracy [3], [12], [13]. It has been reputed for its simplicity and less computational errors. There have been different designs of ANN models to solve specific functional, approximation, and optimization problems. This ranges from Adaptive Linear Element (ADALINE) neural network, Multi-Layer Perceptron (MLP) neural network, Radial Basis Function (RBF) neural network, Generalized Regression Neural Network (GRNN) etc. [14]. The MLP-ANN application in system modeling and predictions has demonstrated superiority in solving optimization and prediction problems over the years [13], [15].

However, one of the major drawbacks of MLP-ANN is overlearning, which results from inappropriate architectural selection [16]. Adoption of MLP-ANN in systems modeling also requires accurate selection of the required architectural compositions for the proper model building to ensure good training performance, especially as it has not shown proficiencies in incoherent dataset handling [17]. Noise in the dataset leads to dataset degradation and is majorly introduced during data transmission due to noisy channels and errors encountered in the course of measurement and quantization [18]. There is always need for dataset de-noising of the measurement data to improve its quality. These can be achieved through various methods such as multi-fractal analysis, filtering the dataset using filters, applying wavelength analysis, etc. [19]. Filters play a significant role in the dataset restoration process by convolution and application of moving window principles. Filters can either be linear or non-linear filters with each having it merits and demerits. The linear filter is made up of mean and Least Mean Square (LMS) filters, while the non-linear filter is made up of median filters [20].

An adaptive ANN model that uses an MLP-ANN built on non-linear Vector Median Filter (VMF) termed as model-1 is designed and implemented in this research work compared with trained conventional MLP-ANN model termed model-2 trained without filtering. The two models, which are model-1 for improved prediction signal power loss via ANN training using noise-free dataset achieved through filtering and dataset de-noising and conventional MLP-ANN were designed, trained, and analysis made. The performance analytical comparison of the two models was made using measurement data from 1900 MHz frequency band from a Line-of-Sight (LOS) location-1 and Non-Line-of-Sight (NLOS) location-2 micro-cell Long Term Evolution (LTE) environments. The Levenberg-Marquardt (LM) for network optimization and Bayesian Regularization (BR) algorithms, an improvement of LM algorithm, was adopted for the model training. The organization of the research work is as follows: Section II discusses the basics of dataset de-noising, employed training algorithms, and the procedure of data collection. Section III has the proposed system model for this work. Section IV has the statistical and graphical results and discussions of the network model training. Finally, Section V concludes the work and recommends the future aspect.

II. Basics of Dataset De-Noising and Training Methods with Data Collection Process

Electromagnetic signal de-noising manipulates the dataset to produce a higher quality dataset by filtering the unwanted signals inform of noise [18]. Noise is simply data without meaning or an unwanted signal recorded during dataset measurement, resulting from malfunction electronic during data acquisition or error in the transmission of a dataset through channels [21]. A noise-free and de-blurred dataset needs to ensure higher quality data for useful measurement dataset processing before ANN training. Filters are used for noise suppression, while there can either be a linear or non-linear filter. Linear filters show poor performance in non-additive noise, just like in systems that face non-linearity and non-Gaussian statistics [21].

Various non-linear filters have been designed in [15], [18], [21] to conquer the inadequacies of linear filters. The designed non-linear filter helps in dataset noise removal and data transformation, which helps in raw dataset manipulation to generate single input, which has been used for the ANN training for improved output results. The aim is to generate slow changes in data values for an easy understanding of data trends.

A. Non-Linear Median Filters

The non-linear median filters operate with the principles of moving window principles with all the pixel values sorted from the surrounding neighborhood to numerical order and the pixel being replaced in consideration to the middle pixel value [15], [18], [21]. The median of the pixel in the window is calculated and the pixel center window being replaced using the calculated median value. The non-linear median filter is mathematically stated as:

$$g(p) = median\left\{ f(p), wherep \in N_8(p) \right\} \quad (1)$$

where $g(p)$ is the value of the median pixel, $f(p)$ is the values of the pixel under the mask, $N_8(p)$ is the 8-neighbor of pixel 'p'. The non-linear median filters lessen random impulsive noise without edges blurring as obtainable using linear filters, thus providing a dataset.

B. Training Algorithm Employed

In this research work, authors are using below 2 training algorithms.

1) Levenberg-Marquardt training algorithm

Levenberg-Marquardt (LM) training algorithm is one the training algorithms applied in training the designed models. The LM training algorithm is a back propagation algorithm employed for error function minimization [22], [23]. It is derived from the Gauss-Newton and gradient descent method that determine the right combination for an excellent generalization of the network through linear permutation of squared error and weight variables minimization. In agreement with the cost function, the method of Newton's weight update is described as:

$$\nabla w = -\left[H(m)\right]^{-1} g(v) \tag{2}$$

where *H(m)* signifies the Hessian matrix *g(v)* and signifies the gradient vector as:

$$H(m) = J(m)^T J(m) + Q(m) \tag{3a}$$

$$g(v) = J(m)^T e(f) \tag{3b}$$

J(m) stand for Jacobian matrix:

$$Q(m) = \sum_{i=1}^{n} \nabla^2 e(f) e(f)^T \tag{3c}$$

Eq. (2) can be written as:

$$\nabla w = -\left[J(m)^T J(m) + \mu I\right]^{-1} J(m)^T e(f) \tag{3d}$$

This is the LM weight update, the identity matrix is I and the damping factor is μ.

2) Bayesian regularization training algorithm

The Bayesian Regularization (BR) training algorithm updates ANN model weight and bias according to LM optimization [23]. It regulates linear combination to guarantee enhanced generalized network when compared with LM training algorithm. The modification of the damping factor from the LM training algorithm function approximation technique of Eq. (3) for the optimization process is at every iteration. There is also cost function increase by the introduction of Bayesian hyper-parameter: the beta and alpha parameters to search for minimal error using smallest weight and reports best learning process direction. The cost function is:

$$F = \beta E_d + \alpha E_s \tag{4}$$

where E_d stands for the sum of squared error while E_s is stands for the sum of squared weight.

C. Data Collection Procedure, Model-1 and Model-2 Training

The field data were collected from a LTE network in microcell environments. Data were collected from two operational Base Station (BS) of LOS and NLOS, that operates at 1900 MHz frequency band. Drive test was employed using appropriate equipment such as a Network scanner, GPS, Laptop augmented with Telephone Mobile Network (TEMS, 1.5.1 version). The measured signal power were gotten along the different route of both the NLOS and the LOS. A total of 2500 and 1800 signal power points were extracted for analysis, applying Map Info and Microsoft Excel Spreadsheet from location-1 and location-2, respectively. The measured signal power represented as Reference Signal Receive Power (RSRP) is related to path loss by:

$$P_{tx} - G_t - G_r - L_t - L_r + Pl \tag{5}$$

where G_t is transmitter gain and G_r is receiver gain, L_t is receiver feeder loss and L_r is transmitter loss, Pl is path loss. and P_{tx} is BS transmit power. (see Table I)

TABLE I. PARAMETERS EMPLOYED

Parameter	Location-1	Location-2
Operating Frequency (MHz)	1900	1900
Base station Antenna Height (m)	40.0	35.0
Base station Antenna gain (dBi)	17.0	16.5
Transmit Power (dB)	43.0	43.0
Transmit cable loss (dB)	0.5	0.5
Feeder Loss (dB)	3.0	3.0
Mobile antenna height (dB)	1.3	1.3
Distance covered	1400	1800

The measured dataset was trained using the early stopping method, divided into three parts in the ratio of 80:10:10 to tackle the problem of over-fitting during network training. The 80% of dataset was used for training, 10% of the data was used for testing and the remaining 10% used for validation. The datasets were trained in ANN toolbox using the 2015a Matrix Laboratory (MATLAB) software platform where the ANN were implemented. Four statistical indices, Standard Deviation (SD), Root mean squared error (RMSE), Mean absolute error (MAE), and the coefficient of Correlation (r) were employed for prediction analysis. These statistical indices are related as follows [2], [6], [23]:

$$SD = \sqrt{\left(\frac{1}{S}\sum_{o=1}^{S}\left|d_o - a_o\right| - MAE\right)^2} \tag{6a}$$

$$RMSE = \frac{1}{S}\sqrt{\sum_{o=1}^{S}\left[d_o - a_o\right]^2} \tag{6b}$$

$$MAE = \frac{1}{S}\sum_{o=1}^{S}\left|d_o - a_o\right| \tag{6c}$$

$$r = \frac{\sum_{o=1}^{N}\left(d_o - \overline{d_o}\right)\left(d_o - \overline{a_o}\right)}{\sqrt{\left[\sum_{o=1}^{S}\left[do - \overline{do}\right]^2\right]\left[\sum_{o=1}^{S}\left[do - \overline{a_o}\right]^2\right]}} \tag{6d}$$

where d_n is normalized data value d_o original data value,. The statistical indices are used to analyze the prediction powers of the models used for ANN training. d_o is desired, a_o is actual network output. $\overline{a_o}$ is mean of the actual output and $o = 1,2, 3, \ldots\ldots s$, which are values of measured signal power.

III. System Design

An adaptive non-linear vector median filter built on MLP-ANN termed model-1 for signal de-noising before ANN training is designed in this research work and comparing their performances with trained single hidden layer conventional MLP-ANN model termed model-2. The non-linear median filter is termed VMF. The development of the algorithm for the design is as follows: de-noising of the normalized dataset using non-linear VMF built on MLP-ANN for training and training of the conventional single hidden layer MLP-ANN with the original data set. A comparison of the performances of the two models were made. Both the models were progressively employed through various iterations.

A. Vector Median Filter (VMF)

The VMF is a robust non-linear filter for signal de-noising that performs well with unknown noise type and characteristics [21], [24]. For Q of x_i, observation, where $i = 1, 2, 3, \ldots\ldots, Q$, the median of the dataset x_i is expressed as:

$$f(x) = \sum_{i=1}^{Q} |x_i - x| \tag{7}$$

where $f(x_{med}) \leq f(x_i) \vee x_i x_{med} \in \{x_i, i = 1, \ldots. Q\}$, x_i defines the vector k dimension $\{x_i, x_{i2}, x_{i3}, \ldots\ldots x_{ik}\}^T$.

B. Multi-Layer-Perceptron Artificial Neural Network (MLP-ANN)

The MLP-ANN has shown outstanding performances in solving problems of non-linear optimization [25], [26]. Architecturally, the MLP-ANN is made up of input, hidden and output layers. The three layers are interconnected, the hidden or middle layer being either single or multiple. A major component of MLP-ANN is the processing unit comprising of neurons that are connected using weights [24]. An activation function is applied in the description of the neurons being fed to the input unit. If an input index h is considered, Q being the output from the hidden layer, then the overall output layer output is computed as:

$$y = a_o\left(\sum_{j=0}^{n} w_{hQ}\left(a_h \sum_{i=0}^{n} w_{oQ} I_i\right)\right) for Q = 1, 2 \ldots n \tag{8}$$

where w_{hQ} and w_{oQ} are the connection weight and the synaptic weight vectors of the hidden layer neuron input and the hidden layer neuron output, respectively. i denotes input vector, $i=1, 2, \ldots., n$. a_o and a_h denotes the output layer and hidden layer activation function, respectively.

There is a minimization of error function during the MLP-ANN training and this is expressed as:

$$E(w) = \frac{1}{2}\sum(y_t - v_t) = \frac{1}{2}\sum_{v=1}^{n} e_t^2 \tag{9}$$

where y_t and v_t denotes the desired output target and the actual network value, respectively. It has been represented as $e_t = y_t - v_t$.

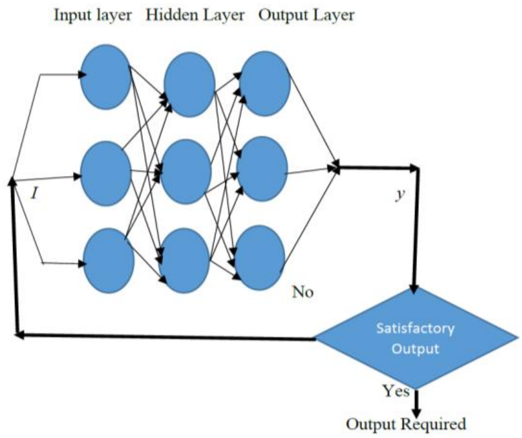
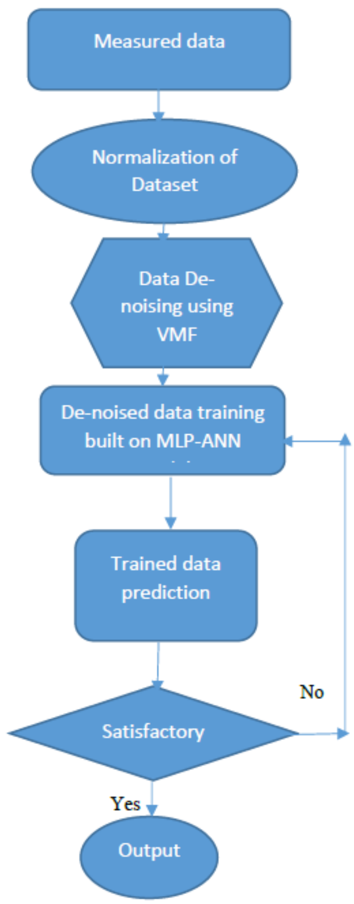
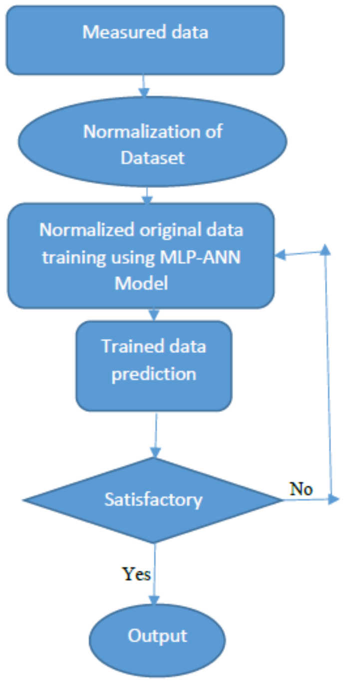


Fig. 1. The MLP-ANN with single hidden layer.



(a)



(b)

Fig. 2. Built ANN models for dataset training (a) VMF built on MLP-ANN model for de-noising dataset (b) conventional MLP-ANN model trained with original dataset.

Firstly, the measured dataset were normalized to the ensured application of standardized dataset. Thereafter, the standardized dataset were pre-processed for building VMF built on MLP-ANN model-1 by de-noising the dataset for training. The second model-2, the conventional MLP-ANN was trained using an original standardized dataset without de-noising. The processed and un-processed datasets were fed to model-1 and model-2, respectively. The predictive abilities of the two trained models were analyzed and comparisons made.

IV. Statistical and Graphical Results and Discussion

A. *Statistical Presentation*

The statistical analysis of the result from the trained Model-1 and Model-2 using the four first order statistical indices are shown in Table II.

B. *Graphical Result Presentations*

Graphical results presentation for signal power loss prediction performance of model-1 and model-2 in the same graph using LM and BR training algorithms for performance analysis in LOS location-1and NLOS location-2 are presented in Fig. 3 and Fig. 4, respectively.

The prediction results from model-1 and model-2 training are shown graphically in Fig. 3 for LOS location-1 and in Fig. 4 for NLOS location-2. The statistical results using 1st order statistical indices, SD, RMSE, MAE and r are shown in Table II for model-1 and model-2 of LOS and NLOS location-1 and location-2, respectively. The SD shows the variation in measured data and prediction results while the RMSE compares the measured data and prediction values. The MAE determines the closeness of prediction values to measured values, while r indicates the strength of connection of the prediction values to measured values. The closer the *r* is to 1 shows a strong connection of the prediction values to measured values.

TABLE II. PREDICTION PERFORMANCES OF VMF-MLP MODEL-1 AND MLP-ANN MODEL-2 USING 1ST ORDER STATISTICAL INDICES

Artificial neural network training	MODEL 1: VMF-MLP (LOS)		MODEL 1: VMF-MLP (NLOS)		MODEL 2: MLP-ANN (LOS)		MODEL 2: MLP-ANN (NLOS)	
TRAINING ALGORITHM	**TRAIN LM**	**TRAIN BR**	**TRAIN LM**	**TRAIN BR**	**TRAIN LM**	**TRAIN BR**	**TRAIN LM**	**TRAIN BR**
SD	1.318	1.200	1.520	1.480	1.520	1.500	1.670	1.580
RMSE	2.305	2.200	2.490	2.290	2.600	2.480	2.690	2.500
MAE	1.740	1.300	1.780	1.440	2.210	1.890	2.220	1.900
r	0.990	0.995	0.965	0.980	0.960	0.975	0.930	0.950

From Table II, the presented statistical results show an improved prediction results training with model-1 in comparison to training with model-2 for both LOS location-1 and NLOS location-2. For instance, the coefficient of correlation *r* for LOS location-1 is 0.990 using *trainlm* and 0.995 using *trainbr* for the designed Model-1 compared to training using Model-2 which gives 0.960 training with *trainlm* and 0.975 training the model with *trainbr*. There are stronger connections of the measured data to the prediction values obtained employing designed Model-1 compared to Model-2 while applying the 1st order statistical indices for prediction analysis. The same patterns of predictions were seen for both location-1 and location-2 considering other 1st order statistical indices employed.

Furthermore, comparison of Model-1 and Model-2 training with BR algorithm (*trainbr*) gives improved prediction results in comparison to training with LM algorithm (*trainlm*). This validates that BR though updates ANN weights and bias in agreement with LM optimization further regulates linear combination, thereby guaranteeing improved generalized network for better prediction results.

The pattern of data spreading for trained designed Model-1 and Model-2 for LOS location-1 and NLOS location-2 are shown in Fig. 3 and Fig. 4, respectively. The signal power is seen to propagate steadily across various distances for LOS as shown in Fig. 3 while there are some distortions in relation to smooth electromagnetic signal propagation for NLOS location-2 as shown in Fig. 4. Such should be considered by network engineers during network planning and upgrade for improved signal power transmission. The superior performance of Model-1 compared to Model-2 during training using BR algorithm is also clearly seen in both graphical presentations for LOS in Fig. 3 and NLOS in Fig. 4, respectively. The orange color, which overshadows other colors represent training with BR algorithm using model-1.

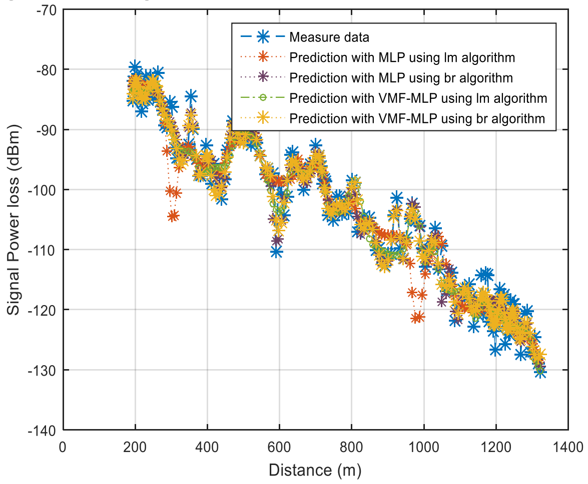


Fig. 3. Measured signal power loss prediction with VMF-MLP and MLP-ANN using LM and BR algorithm for LOS location-1.

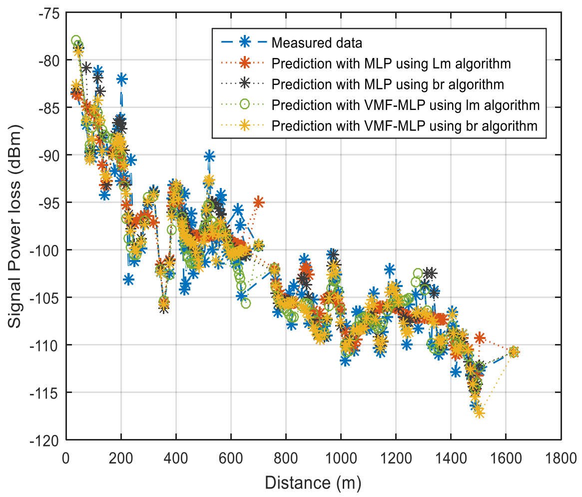


Fig. 4. Measured signal power loss prediction with VMF-MLP and MLP-ANN using LM and BR algorithm for NLOS location-2.

V. Conclusion and Future Recommndations

This research work analyzed the performance of a designed non-linear vector median filter built on MLP-ANN termed model-1 and a conventional MLP-ANN model termed model-2. The vector median filter was adopted for dataset de-noising to ensure an enhanced dataset before network training. Data de-noising is a method employed for the removal of unwanted signal inform of noise from measured dataset to ensure improved dataset for model training. The ANN model training demonstrates enhanced prediction of signal power loss using VMF built on MLP compared to training with conventional MLP-ANN. An early stopping method was adopted during the training process in the ratio of 80:10:10 to ensure better network generalization.

The Levenberg Marquardt and Bayesian Regularization training algorithms were employed and their training performances compared. Two locations comprising of Line-of-Sight and non-line-of-sight were considered during data measurements. The 1st order statistical indices were adopted for prediction analysis and results clearly demonstrate enhanced signal power loss prediction using the designed VMF built on MLP compared to conventional MLP.

Future research work will investigate the effect of the architectural composition of other ANN models in the enhancement of signal power loss prediction.

Conflict of Interest

The authors declare no conflict of interest.

Authors Contributions

Virginia C. Ebhota (VCE) and Viranjay M. Srivastava (VMS) conducted this research. VCE trained and analyzed the model with data and wrote the paper, VMS has verified the result with the designed model. All authors had approved the final version.

References

[1] E. Amaldi, A. Capone, and F. Malucelli, "Radio planning and coverage optimization of 3G cellular networks," *Wireless Networks*, vol. 14, pp. 435-447, 2008.

[2] J. Isabona and V. M. Srivastava, "Coverage and link quality trends in suburban mobile broadband HSPA network environments," *Wireless personal Communication*, vol. 95, no. 4, pp. 3955-3968, Aug. 2017.

[3] N. Aleksandar and N. Natasa, "Micro-cell electric field strength prediction model based upon artificial neural networks," *International Journal of Electronics and Communications* vol. 64, pp. 733–738, 2010.

[4] J. P. Kiran, D. N. Vishal, and G. Rajkot, "Comparative analysis of path loss propagation models in radio communication," *International Journal of Innovative Research in Computer and Communication Engineering*, vol. 3, 2015.

[5] C. Phillips, D. Sicker, and D. Grunwald, "A survey of wireless path loss prediction and coverage mapping methods," *IEEE Communication Survey & Tutorials*, vol. 15, no. 1, pp. 255-270, 2013.

[6] V. C. Ebhota and V. M. Srivastava, "Performance analysis of learning rate parameter on prediction of signal power loss for network optimization and better generalization," *Wireless Personal Communications*, vol. 116, no. 2, pp. 1111-1128, May 2021.

[7] C. K. Jha and R. Jain, "Literature survey on various outdoor propagation model for fixed wireless network," *International Journal of Science and Research*, vol. 3, no. 8, pp. 1601-1604, Aug. 2014.

[8] T. A. Benmus, R. Abboud, and M. K. Shater, "Neural network approach to model the propagation path loss for

great tripoli area at 900, 1800, and 2100 MHz bands," in *Proc. 16th International Conference on Sciences and Techniques of Automatic Control and Computer Engineering*, Monastir, Tunisia, 21-23 Dec. 2015, pp. 793-798.

[9] I. Khan, T. C. Eng, and S. A. Kamboh, "Performance analysis of various path loss models for wireless network different environments," *International Journal of Engineering and Advanced Technology*, vol. 2, no. 1, pp. 161-165, Oct. 2012.

[10] J. C. Ogbulezie, M. U. Onuu, J. O. Ushie, and B. E. Usibe, "Propagation models for GSM 900 and 1800 MHz for port Harcourt and Enugu, Nigeria," *Network and Communication Technologies*, vol. 2, no. 2, pp. 1-10, 2013.

[11] S. Sun, T. S. Rappaport, T. A. Thomas, A. Ghosh, H. C. Nguyen, I. Z. Kovacs, I. Rodriguez, O. Koymen, and A. Partyka, "Investigation of prediction accuracy, sensitivity, and parameter stability of large-scale propagation path loss models for 5G wireless communications," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 5, pp. 2843–2860, May 2016.

[12] V. C. Ebhota and V. M. Srivastava, "Effect of architectural composition of MLP ANN in neural network learning for signal power loss prediction," *Journal of Communications*, vol. 16. no. 1, pp. 20-29, Jan. 2021.

[13] J. Isabona and V. M. Srivastava, "A neural network based model for signal coverage propagation loss prediction in urban radio communication environment," *International Journal of Applied Engineering Research*, vol. 11, pp. 11002-11008, 2016.

[14] V. C. Ebhota, J. Isabona, and V. M. Srivastava, "Investigation and comparison of generalization ability of multi-layer perceptron and radial basis function artificial neural networks for signal power loss prediction," *Internatuionl Journal on Communications Antenna and Propagation*, vol. 9, no. 1, pp. 46-54, Feb. 2019.

[15] V. C. Ebhota and V. M. Srivastava, "Prediction of signal power loss (at micro-cell environments) using generalized adaptive regression and radial basis function ANN models built on filter for error correction," *International Journal on Communications Antenna and Propagation*, vol. 11, no. 2, pp. 94-105, April 2021.

[16] V. C. Ebhota and V. M. Srivastava, "Enhanced error reduction of signal power loss during electromagnetic propagation: Architectural composition and learning rate selection," *Journal of Communications*, vol. 16, no. 10, pp. 450-456, Oct. 2021.

[17] A. Ali, R. Ghazali, and M. M. Deris, "The wavelet multi-layer perceptron for the prediction of earthquake time series data," in *Proc. 13th International Conference on Information Integration and Web-Based Applications and Services*, Ho Chi Minh City, Vietnam, 5-7 Dec. 2011, pp. 138-143.

[18] V. C. Ebhota, J. Isabona, and V. M. Srivastava, "Improved adaptive signal power loss prediction using combined vector statistics based smoothing and neural network approach," *Progress In Electromagnetics Research C*, vol. 82, pp. 155-169, 2018.

[19] V. R. Tripathi, "Image de-noising using non-linear filter," *International Journal of Modern Engineering Research*, vol. 2, pp. 4543-4546, 2012.

[20] N. R. Kumar and J. U. Kumar, "A spatial mean and median filter for noise removal in digital images," *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, vol. 4, pp. 246-253, 2015.

[21] G. Bhumika and S. N. Shailendra, "Image de-noising with linear and non-linear filters: a review," *International Journal of Computer Science*, vol. 10, pp. 1694-0784, 2013.

[22] C. Kanzow, N. Yamashita, and M. Fukushima, "Levenberg-Marquardt methods with strong local convergence properties for solving non-linear equations with convex constraints," *Journal of Clinical and Analytical Medicine*, vol. 172, pp. 375-97, 2004.

[23] F. D. Foresee and Martin T. Haga, "Gauss-Newton approximation to Bayesian learnig," in *Proc. International Conference on Neural Networks*, Huston, USA, 12 June 1997, pp. 1930 - 1935.

[24] N. N. Vijayakumar and B. Plale, "Prediction of missing events in sensor data streams using Kalman filters," in *Proc. 1st International Workshop on Knowledge Discovery from Sensor Data, in conjunction with ACM 13th International Conference on Knowledge Discovery and Data Mining*, 2007, pp. 1-9.

[25] E. Ostlin, H. J. Zepernick, and H. Suzuki, "Macrocell path loss prediction using artificial neural networks," *IEEE Transactions on Vehicular Technology*, vol. 59, no. 6, pp. 2735-2747, July 2010.

[26] B. Triqui and A. Benyettou, "Comparative study between radial basis function and temporal neuron network basic in cardiac arrhythmia," *International Journal on Communications Antenna and Propagation*, vol. 8, no. 2, pp. 186-193, 2018.

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