An Adaptive Vector Median Filtering Approach to Enhance the Prediction Efficiency of Signal Power Loss

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Abstract**—**This research work designed and implemented an adaptive Artificial Neural Network (ANN) model using Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) models built on a Vector Median Filter (VMF) for pre-processing of the dataset. Normalized dataset is denoised using VMF and trained with both MLP- and RBF-ANN models. The proposed model has been developed from measurement data collected from two transmitter locations of non-line-of-sight and line-of-sight operating at *the 1900MHz* frequency band from LTE cellular network over distances of *1800m 1400m* respectively. For non-line-of-sight site-1, VMF-MLP gives a correlation coefficient *of 0.9600* compared to *0.9490* for VMF-RBF with a Bayesian regularization training algorithm. The VMF-MLP has *2.1380, 1.5000,* and *1.4510* for root mean squared error, mean absolute error, and standard deviation compared to *2.3550, 1.5370,* and *1.5610* for VMF-RBF network, respectively. The same trend was seen for line-of-sight in site-2 where correlation coefficient for VMF-MLP is *0.9900* and for VMF-RBF is *0.9840*. The VMF-MLP has root mean squared error, mean absolute error, and standard deviation as *2.0670, 1.4900,* and *1.3180*, respectively, compared to VMF-RBF as *2.3470, 1.9010,* and *1.3760*, respectively. The predictions of these measurement data have been analyzed in this research work.

Index Terms**—**Signal denoising, filtering techniques, vector median filters, multi-layer perceptron, artificial neural network, radial basis function.

I. Introduction

Artificial Neural Network (ANN) models, especially the feed-forward neural network models such as the Multi-Layer Perceptron (MLP) model, on the selection of an appropriate number of hidden layer neurons demonstrates excellent performance in solving non-linearity problems on sets of measurement data [1]-[3]. Likewise, the Radial Basis Function (RBF) ANN that comprises fixed three-layer network architecture has demonstrated the right prediction and excellent generalization in resolving non-linearity problems on sets of measurement data [4]-[6]. However, measurement data are always noisy, this relates to the difficulty in predicting electromagnetic signal power loss and the quality of prediction results using the ANNs [7]. There is degradation in the quality of measurement data as a result of various contamination of noise.

Noise is an unwanted signal, and in data processing, it can be counted as data without meaning, i.e., data that are not employed in signal transmission but produces unwanted by-products of other non-required activities. Noise perverts signal quality in the acquisition, transmission, storage, etc. [8], [9]. For meaningful and useful processing of measurement data before ANN training, there is a need for acquired data to be noise-free and de-blurred to ensure improved data quality. Filters are applied for noise suppression and de-blurring [9]. Filters are either linear or non-linear, with linear filters being mostly in-use in the early day as the basic tool in image and signal processing [10]. However, linear filters perform poorly in the presence of non-additive noise as well as in systems that encounter non-linearities and non-Gaussian statistics. Since the linear filters do not remove impulsive noise efficiently, they tend to distort edges and show poor performance in the presence of signal-dependent noise.

To overcome the shortcomings of linear filter, different types of non-linear filters have been designed by *Ebhota et. al.* and *Tripathi* [11], [12]. Researchers' interest has continued to increase the usefulness of data pre-processing in enhancing training efficiency and prediction skill of ANN based algorithms [11], [12]. Data sampling, which decides for a sub-set representation of the bulky dataset, data normalization that standardizes data for improved sampling, data denoising aids in noise removal from the dataset and data transformation that assists in raw dataset manipulation to generate a single input has been of immense attention in recent time. The MLP-ANN creates global approximations to non-linear input-output mapping, thus they are much capable of generalization in the regions of input space where there is little or no availability of training data while RBF-ANN makes use of exponential decaying non-linearity in the construction of local approximations to non-linear input-output mapping. As a result, RBF-ANN has a faster learning rate but exhibits reduced sensitivity to the presented training data order, Levenberg-Marquardt (LM), and Bayesian Regularization (BR) training algorithms.

Filtering is one of the techniques applied in the area of data smoothing, denoising, and transformation. Other data denoising techniques such as singular spectrum analysis, factor analysis, wavelet multi-resolution analysis, moving average smoothing, etc. have been examined in many previous works [11], [13]-[20]. In

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[20]-[22], the wavelet denoising technique, combined with the ANN model, was utilized to trend the prediction in the rainforest time series dataset. The authors' result shows that a combination of wavelet denoising technique and ANN-based prediction model is more efficient than prediction based on ANN models alone. In [23], the same combination of wavelet and ANN model was applied but for improved prediction of underground water levels and earthquake data. In [16], three data pre-processing techniques: the Moving Average (MA) technique, the Principal Component Analysis (PCA), and the Singular Spectrum Analysis (SSA) were used with modular ANN for enhanced rainfall data prediction. In [23], the effectiveness of dynamic filtering and intricacy on accurate prediction of stereo and video data was proposed and validated. A pre-processing technique on the dataset to study the daily reservoir inflow was applied with results showing an improved prediction accuracy of the reservoir's inflow on the utilization of the pre-processed dataset. In [24], the authors explored the combination of Kalmar filters and dynamic linear models to predict missing occurrences in time series sensor data stream. The result demonstrated that the application of filters with a linear model is a feasible technique in boosting the sensor data's prediction efficiency. In [25], a linear data filtering technique was utilized to analyze and predict cellular network coverage using CDMA2000 signal data, while in [11], a resourceful prediction model built on MLP-ANN with a vector order statistical filter was utilized by the authors for improved prediction of signal power loss in a micro-cellular LTE environment.

Therefore, exploration of the information contained in the dataset by way of pre-processing contributes immensely in the model training enhancement and precision in predictions. Various research focuses have shifted to Artificial Neural Network (ANN) models due to their ability to learn the input-output relationship of non-linear complex systems and their fast-computational speed and efficiency. However, most of the existing research concentrations are on time series datasets that utilize linear smoothing based data filtering and standardization techniques, which does not capture the stochastic non-linearity in many multi-faceted datasets. *Ebhota et. al.* [11] addressed that a combination of non-linear data filtering techniques built on the MLP-ANN model for enhanced prediction of signal power loss in a microcellular environment.

It is seen that there are differences in behavioral patterns in the hidden layer of multi-layer perceptron artificial neural network and radial basis function artificial neural network when trained with Levenberg-Marquardt and Bayesian Regularization algorithms, respectively. The hidden neuron of the radial basis function artificial neural network influences the output only for inputs near its center, requiring an exponential number of hidden neurons to ensure coverage of the entire space. From this assessment, radial basis functions artificial neural network is more suitable for modeling problems with small input numbers. Further training of the artificial neural network with the designed adaptive prediction models: vector median filter- multi-layer perceptron and vector median filter radial basis function artificial neural networks show improved prediction results compared to artificial neural network training with conventional multi-layer perceptron and radial basis function networks, respectively. Their prediction performances compared with conventional multi-layer perceptron and radial basis function artificial neural networks using 1st order statistical indices. In this present research work, two different models, a combination of non-linear data filtering technique built on RBF-ANN and a non-linear data denoising technique built on MLP-ANN, are designed and implemented for improved prediction of signal power loss. There is a comparison of the predictiveness of the two designed models on measurement dataset realized from *1900 MHz* frequency band from a Non-Line-of-Sight (NLOS) and Line-of-Sight (LOS) microcellular Long-Term Evolution (LTE) network environments.

This work has been organized as follows: Section II discusses filters and order statistic filters. Section III describes the proposed system design, with the Vector Median Filter (VMF), the MLP-ANN, and the RBF-ANN concepts, the Levenberg-Marquardt and Bayesian Regularization (BR) algorithms utilized in the work. Section IV measurement signal datasets and measurement procedures have been performed, including the training of the system and their training patterns. Results and performance evaluation of this work has been discussed in the Section V. Finally, Section VI concludes the work and recommends future aspects.

II. Concepts of Signal Denoising And Statistical Filter

A. *The Concept of Signal Denoising*

Signal denoising is the manipulation of signal data to generate high-quality data by leaving out the unimportant (i.e. noise) through filtering [26]-[28]. It has been represented in Fig. 1. Noise in signal data arises due to various factors such as error rate, speed, electronic equipment malfunction, etc. The goal of signal denoising is to generate slow changes in values so that the data trend can easily be understood. There are different existing denoising techniques and algorithms, such as filtering techniques using filters, wavelet-based technique, multifractal techniques, etc. with each having its advantages and disadvantages [29].

Denoising algorithms are application dependent i.e. different filters are constructive to different noise types [11], [29]. The application of filters for denoising has shown to be best when the data is degraded with ‘salt and pepper’ type of noise. Salt and pepper noise are impulse noise, which is also known as spikes. They are caused as a result of an error in data transmission through channels [30]. The salt and paper impulsive noise mostly occur due to electronic malfunction during data acquisition, such as the malfunction of the camera sensors' pixel elements. It can also occur as a result of timing error and faulty memory location during the digitalization process. Salt and pepper impulsive noise only has two possible values, ‘a and b’ with the probability of each being less than *0.1* [11], [29].

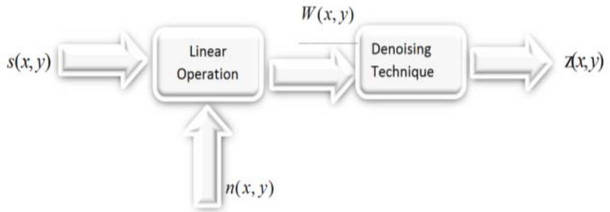


Fig. 1. Sketch of the data denoising concept

There are additive and multiplicative noises [31]. The additive noise follows the rule: $W(x,y)=s(x,y)+n(x,y)$, where $s(x,y)$ represents the original signal/data, $n(x,y)$ represents the noise that degrades the acquired signal $W(x,y)$ and (x,y) represent the pixel location. Salt and pepper noise and Gaussian Uniform are examples of additive noise. Multiplicative noise satisfies the rule: $W(x,y)=s(x,y)\times n(x,y)$. Speckle noise is an example of multiplicative noise. The signal/data $s(x,y)$ is blurred by linear operation and introduced noise $n(x,y)$ to generate degraded data $W(x,y)$. $W(x,y)$ is convolved with the process of restoration $g(x,y)$ to generate restored data $z(x,y)$.

B. Linear and Non-Linear Filtering Techniques

The Linear filter comprises of the mean filters and the Least Mean Square (LMS) adaptive filters [11], [31]. The non-Linear filters are based on Median filters. Filters play a key role in the data restoration process with the major concept being digital convolution using linear filters and the moving window principle. If $w(x)$ is the input signal subjected to filtering and and $h(t)$ is the impulse response, then the filtered output z(x) can be expressed as [17]:

$$z(x)=\int w(t)h(x-t)dt \tag{1}$$

This integral represents a convolution integral which can be expressed as [17]:

$$z=w^{*}h \tag{2}$$

For two dimensional cases, $h(t)$ can be replaced with $h(t,u)$, therefore Eq. (1) becomes [17]:

$$Z(i,j)=\sum_{t=i-k}^{i+k}\sum_{u=j-l}^{j+l} w(t,u)h(i-t,j-u) \tag{3}$$

Values of $h(t,u)$ denote filter weight, filter kernel, and a filter mask. The sum output is created by a series of shift-multiply operations, which form the discrete convolution.

(i) Mean Filtering - The mean filters operate on the principle of shift-multiply sum, it acts on data by smoothing, thereby reducing the variation of intensity between adjacent pixels [30]. Mean filtering is implemented based on digital convolution by applying linear filters, which give a result that is the weighted sum of the pixel values and its neighbors. The kernel or the mask is a square, if the sum of the masking coefficient is *1*, then the average quality of the data is not altered. However, if the coefficient is *0*, then the average data quality is lost and returns degraded data.

Computation of straightforward convolution of data with the kernel carries out the process of mean filtering. Mean filtering is beneficial when the noise signal/data is “salt and pepper” i.e. impulsive noise. It operates like a low pass filter, not permitting the high-frequency components present in noise to pass through. Large kernel sizes of 5x5 or 7x7 yields more denoising, however, it makes the data more blurred. Therefore, a tradeoff is usually made between kernel size and the amount of denoising [29], [30].

(ii) Least Mean Square (LMS) Adaptive Filters - The weight of the LMS adaptive filters changes after every iteration, unlike in mean filters where it remains constant [32]. LMS adaptive filters are efficient in non-stationary data denoising i.e. datasets with a swift change in density. There is iterative parameter adjustment in LMS adaptive filtering during the data scanning process to match the data generating mechanism. Like the mean filter, the LMS adaptive filter performs well for data degraded with “salt and pepper” type of noise, however, this filter performs better denoising task in comparison to mean filters [14], [17], [33].

(iii) Median Filter (Non-Linear Filter) - In median filtering, all the pixel values are sorted from the surrounding neighborhood into numerical order, and the pixel is replaced considering the middle pixel value [31], [34]. The median filters follow the moving window principle, which is alike to mean filter. The 3x3, 5x5, or 7x7 kernel or filter mask of pixels is scanned over the entire dataset's pixel matrix. The median of a pixel in the window is calculated, and the pixel center window is replaced with the calculated value of the median. Mathematically, the median filter can be represented as [35]:

$$g(p)=median\left\{f(p), wherep\in N_{8}(p)\right\} \tag{4}$$

where $g(p)$ is the median pixel value, $f(p)$ is all the pixel values under the mask, $N_8(p)$ is the 8-neighborhood of pixel 'p'. Median filter reduces random impulsive noise without blurring edges as obtainable with mean and LMS adaptive filters [12]. It overcomes the problem of data blurring by proving the clarity of the dataset after denoising [36].

III. Proposed System Design

In this work, the authors have designed an adaptive ANN model using MLP-ANN and RBF-ANN designed on a Vector Median Filter (VMF) for dataset denoising. These are termed VMF-MLP and VMF-RBF, respectively. The algorithm for the design is developed as follows: the normalized dataset is denoised using VMF and trained with both MLP-ANN and RBF-ANN and their prediction performance comparison made. Both the noise filtering technique and the MLP-ANN and RBF-ANN are progressively employed through several iterations.

A. Vector Median Filter (VMF)

The VMF is a robust placed order filter for signal data denoising which performs well with unknown noise sorts and characteristics [35], [37]. Given Q observation of x_i, where $i = 1, 2, 3, \ldots\ldots, Q$ the median of dataset x_i is expressed as:

$$f(x) = \sum_{i=1}^{Q} |x_i - x| \tag{5}$$

where $f(x_{med}) \leq f(x_i) \nu x_i x_{med} \in \{x_i, i = 1, \ldots. Q\}$

and x_i defines the k dimensional vector $\{x_i, x_{i2}, x_{i3}, \ldots\ldots x_{ik}\}^T$

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

The MLP-ANNs are generally made up of two main components: the processing units (neurons) and the connection between the processing units (weights) [4]. Architecturally, it comprises an input layer, one or more hidden layers, and an output layer. The transformation $a(ho) = \frac{1}{1 + \exp^{-ho}}$ is known as the activation function, which defines the neuron output when fed with an input [38, 39]. h is the index of the input and o is the output of the hidden layer. The input data are transmitted to the hidden layer (which may be single or more) in a forward direction, and the net output computation can be expressed as:

$$y = a_o\left(\sum_{j=0}^{n} w_{hQ}\left(a_h \sum_{i=0}^{n} w_{oQ} I_i\right)\right) for Q = 1, 2 \ldots n \tag{6}$$

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

The learning and training process using MLP-ANN involves error function minimization. This can be expressed as:

$$E(w) = \frac{1}{2}\sum(y_t - v_t) = \frac{1}{2}\sum_{v=1}^{n} e_t^2 \tag{7}$$

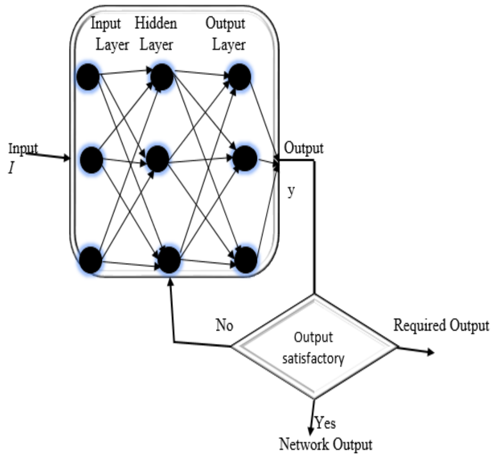
where y_t and v_t signify the desired output target and the actual network value, respectively. It has been represented as $e_t = y_t - v_t$. The network training using MLP-ANN is shown in Fig. 2(a).

C. Radial Basis Function Artificial Neural Network (RBF-ANN)

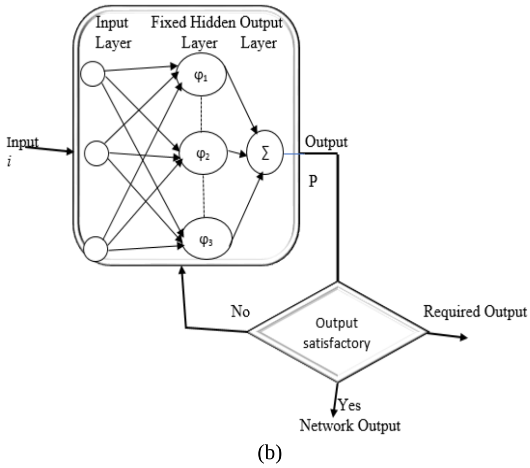
Architecturally, RBF-ANNs are made up of fixed three-layer units. An input layer with one or more predictors with each predictor variable having a separate neuron, a hidden layer containing many neurons and an output layer [11], [40]. The input unit's input data is re-mapped in the hidden layer to ensure they are linearly divisible, and the output layer performs the linear division. Each hidden layer neuron possesses a redial basis function centered at a point dependent on the input-output predictor variables. These neurons have a weight that multiplies the hidden layer values and are summed and hands over to the output layer. Input weights w^h is weighted by the input vector i, considering the input to the hidden layer S_H expressed as:

$$S_H = \left(i_1 w_{1,H}^h \, i_2 w_{2,H}^h \ldots\ldots\ldots i_{m-1} w_{m-1,H-1}^h \, i_m w_{m,H}^h\right) \tag{8}$$

where m and S_H are input and hidden unit index, respectively. i_m is the m^{th} input, $w_{m,H}^h$ is the input weight between m and the hidden unit S_H.



(a)



(b)

Fig. 2. Training of (a) Multi-layer perceptron ANN with one hidden layer (b) Radial Basis Function ANN.

The output of the hidden unit is computed as [41]:

$$\varphi_H\left(S_H = \exp\left\{ \frac{\| S_H \left| C_H \right\|^2}{\sigma_H} \right\} \right) \tag{9}$$

where φ_H is the hidden unit activation function, which is normally selected as the Gaussian function, C_H is the center of the hidden unit and σ_H is the hidden unit width.

The index of the output unit P is expressed as:

$$O_P = \sum_{n=1}^{H} \varphi_H\left(S_H\right) W_{HP}^0 + W_{0P}^0 \tag{10}$$

where W_{HP}^0 is the output weight between hidden unit and output unit, w_{0P}^0 is the bias weight of the output unit. The network training using RBF-ANN is shown in Fig. 2(b).

D. Levenberg-Marquardt and Bayesian Regularization Back Propagation Training Algorithms

In this training the designed models (Levenberg-Marquardt and Bayesian Regularization algorithms) are utilized. The Levenberg-Marquardt algorithm is a back-propagation training algorithm specifically applied for the minimization of error function [42]. The algorithm is from Gauss-Newton and gradient descent technique and determines the correct combination to give a good generalization of the neural network by minimization of linear permutation of squared error and weight variables. In conformity to the cost function, Newton's technique weight update is known as:

$$\nabla w = -\left[H\left(m\right)\right]^{-1} g\left(v\right) \tag{11}$$

where $H(m)$ and $g(v)$ denote the Hessian matrix and the gradient vector, respectively shown as:

$$H\left(m\right) = J\left(m\right)^T J\left(m\right) + Q\left(m\right) \tag{12}$$

$$g\left(v\right) = J\left(m\right)^T e\left(f\right) \tag{13}$$

$$Q\left(m\right) = \sum_{i=1}^{n} \nabla^2 e\left(f\right) e\left(f\right)^T \tag{14}$$

where J(m) is the Jacobian matrix. If $S(w) = 0$ for Gauss-Newton technique, then equation (11) becomes:

$$\nabla w = -\left[J\left(m\right)^T J\left(m\right) + \mu I\right]^{-1} J\left(m\right)^T e\left(f\right) \tag{15}$$

This is the LM weight update, I is the identity matrix and μ is the damping factor. On the other hand, BR algorithm update weight and bias in agreement with LM optimization [43], [44]. It adjusts linear combination to guarantee an improved generalized network compared to the LM algorithm at the end of network training. From the LM algorithm function approximation technique of Eq. (15), the damping factor modification for the optimization process is all iteration. There is an increase in cost function by the introduction of Bayesian hyper-parameter: alpha and beta to search for minimal error by use of the smallest weight and notify the best direction for the learning process to follow. The cost function becomes:

$$F = \beta E_d + \alpha E_s \tag{16}$$

where E_d is the sum of squared error, E_s is the sum of squared weight.

E. Combination of Vector Median Filter with MLP-ANN and RBF-ANN

The proposed predictive models are termed as vector median MLP-ANN and vector median RBF-ANN. The proposed signal power loss prediction using designed vector median filters built on MLP-ANN and RBF-ANN are set-up as shown in Fig. 3(a) and Fig. 3(b), respectively.

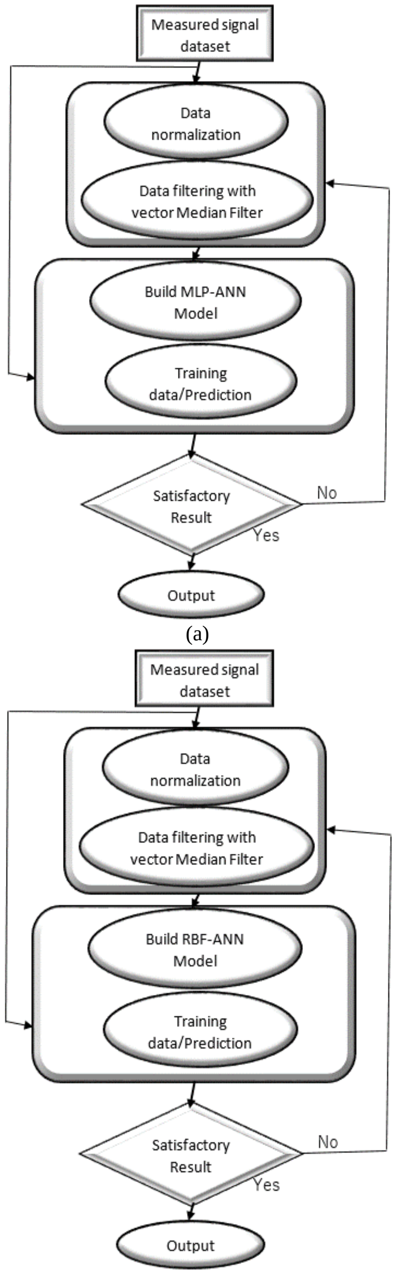


Fig. 3. Proposed Filtering Technique using (a) VMF-MLP and (b) VMF-RBF neural networks.

The measured datasets are first standardized by data normalization and then pre-processed via filtering using a vector median filter. The filtered datasets are fed to the MLP-ANN and RBF-ANN, respectively, for training and prediction. The Prediction efficiency of the designed vector median filter built on MLP-ANN and RBF-ANN is compared, and their predictive ability compared to training with the conventional MLP and RBF is also made.

IV. Data Collection & Neural Network Training with MLP, RBF, VMF-MLP, and VMF-RBF ANN

The field measurements were done from the LTE cellular network around two operational Base Stations (BS) of NLOS and LOS operating at a frequency band of *1900 MHz*. The range of the BS antenna height is *45 m* and *30 m*, which are elevated above the ground level for signal broadcast. Using the drive test with the appropriate equipment, measurement of signal power was conducted, accessed, and extracted along various routes round the cell sites. This was at both NLOS and LOS routes, considering both obstruction and no obstructions between BS and Receiver Station (RS). The equipment includes a Global Positioning System (GPS), network scanner, mobile handsets, and laptop enhanced with Telephone Mobile Software (TEMS, 1.5.1 version). A total of 2,050 and 1,960 signal data points were extracted for analysis using Map Info and Microsoft Excel spreadsheet for site-1 and site-2, respectively. The signal power was measured as Reference Signal Receive Power (RSRP), which relates to propagation path loss by:

$$P_{tx} - G_t - G_r - L_t - L_r + Pl \tag{17}$$

TABLE I. MEASUREMENT PARAMETERS

Parameter	Site-1	Site-2
Operating Frequency (MHz)	1900	1900
Base station Antenna Height (m)	45.0	30.0
Base station Antenna gain (dBi)	17.5	17.5
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)	1.5	1.5

where G_t and G_r are the transmitter gain and receiver gain, L_t and L_r are the receiver feeder loss and transmitter loss, Pl is the propagation pathloss. P_{tx} is the BS transmit power.

For effective network training, the measured signal dataset was divided into three parts in the ratio of 70:15:15, adopting an early stopping technique to address the over-fitting problem during network training. Overall, 70% of the data was used for training, while 15% was used for testing, and the remaining 15% used for validation. The datasets were trained in a 2015a Matrix Laboratory (MATLAB) software platform, where the models were implemented. The LM and BR training algorithms are employed to determine the training capabilities of the examined MLP, RBF, VMF-MLP, and VMF-RBF neural network models at 0.005% learning rate.

The measured dataset was normalized before the signal denoising and neural network training to improve the training phase of the network using the vector normalization technique expressed as:

$$d_n = \frac{d}{\sqrt{\sum_{l=1}^{n} (d_o)}} \tag{18}$$

where d_n and d_o are the normalized data value and the original data value, respectively. Four statistical indices were employed to examine the accuracy of the neural network training predictions. These are the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE), the Standard Deviation (SD) and the correlation coefficient (r). The indices are defined as [45], [46]:

$$RMSE = \frac{1}{S}\sqrt{\sum_{o=1}^{S}\left[d_o - a_o\right]^2} \tag{19}$$

$$MAE = \frac{1}{S}\sum_{o=1}^{S}\left|d_o - a_o\right| \tag{20}$$

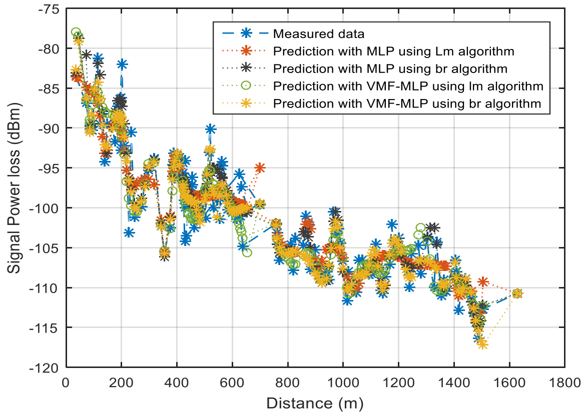
$$SD = \sqrt{\left(\frac{1}{S}\sum_{o=1}^{S}\left|d_o - a_o\right| - MAE\right)^2} \tag{21}$$

$$r = \frac{\sum_{o=1}^{N}\left(d_o - \overline{d_o}\right)\left(d_o - \overline{a_o}\right)}{\sqrt{\left[\sum_{o=1}^{S}\left[do - \overline{do}\right]^2\right]\left[\sum_{o=1}^{S}\left[do - \overline{a_o}\right]^2\right]}} \tag{22}$$

where d_o and a_o are the desired and actual network output respectively. $\overline{a_o}$ is the mean of the actual output and o = *1,2, 3, ………. s*, which are values for samples of signal power.

V. Result and Analysis of the Designed Model

The results from MLP, RBF, VMF-MLP, VMF-RBF utilized to learn and predict the measure data (LTE signal power) has been presented in this section. Fig. 4 represents the measured signal power and the prediction with MLP, RBF, VMF-MLP and VMF-RBF using LM and BR algorithms for performance comparisons in site-1 covering a NLOS. Fig. 5 analyses the similar learning and prediction for site-2 covering a LOS. Table II and Table III show the prediction results for each of the sites using 1st order statistical indices. A closer value of the r to *1* indicates strong connection of the prediction values to the measured data. The RMSE shows the difference between the measured data and the prediction values, the MAE shows the closeness of the prediction values to the measured data, while the SD shows the amount of variation between the measured data and the prediction values. Therefore, the lower the values of RMSE, MAE, and SD, the closeness of the measured data.



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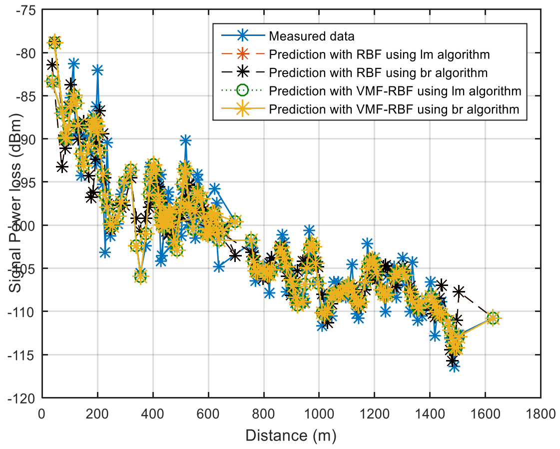
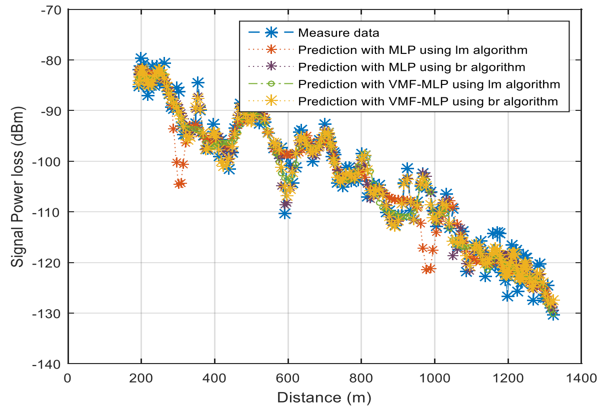


(b)

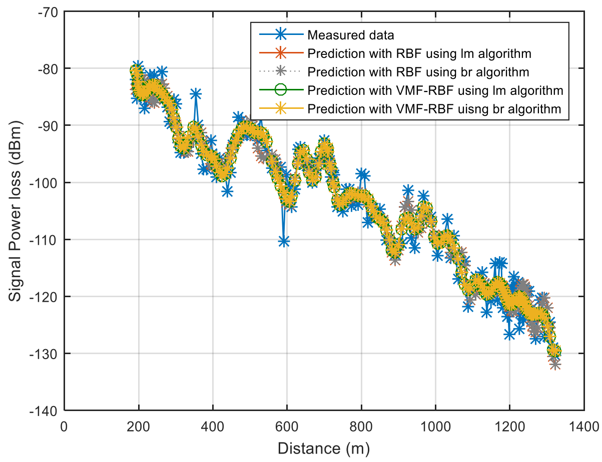
Fig. 4. Measured signal power and prediction with (a) MLP and VMF-MLP (b) RBF and VMF-RBF using LM and BR algorithm at NLOS site-1.

From Table II and Table III, it is seen that the overall training of the MLP and VMF-MLP artificial neural networks models for site-1 and site-2 have improved prediction and generalization of the measured signal power using BR algorithm in comparison to LM algorithm. It is established that VMF-MLP has the highest *r* of *0.9600* and *0.9900* when the network was trained with BR algorithm compared to *0.9420* and *0.9810* when the network was trained with the LM algorithm in site-1 and site-2, respectively. These show that BR algorithm in accordance with LM optimization adjust weights and linear combination to guarantee an improved network generalization compared to the LM algorithm, which only minimizes linear permutation of squared error.

In training the RBF and VMF-RBF neural network models, the input data is re-mapped in the hidden layer to ensure linear divisibility of the data which are linearly divided at the output unit. Therefore, each of the neuron radial basis function is dependent on the input-output predictor variables. The RBF-ANN makes use of exponential decaying non-linearity in the construction of local approximations to non-linear input-output mapping. As a result, RBF ANN has a faster learning rate but exhibits reduced sensitivity to the presentation training data order using the LM and BR training algorithms. The RBF-ANN's hidden neuron influences the output only for inputs near to its center, therefore requiring an exponential number of hidden neurons to ensure coverage of the entire space.



(a)



(b)

Fig. 5. Measured signal power and prediction with (a) MLP and VMF-MLP (b) RBF and VMF-RBF using LM and BR algorithm at LOS site-2.

TABLE II. PREDICTION RESULT WITH MLP, RBF, VMF-MLP, AND VMF-RBF AT NLOS SITE-1

ANN Training	MLP		RBF		VMF-MLP		VMF-RBF	
Algorithms/Prediction Indices	trainlm	trainbr	trainlm	trainbr	Trainlm	trainbr	trainlm	trainbr
R	0.9330	0.9500	0.9210	0.9210	0.9420	0.9600	0.9490	0.9490
RMSE	2.7040	2.4050	2.9420	2.9420	2.5470	2.1380	2.3550	2.3550
MAE	2.0700	1.7100	2.2990	2.2990	1.8010	1.5000	1.5370	1.5370
SD	1.7410	1.6910	1.8360	1.8360	1.8010	1.4510	1.5610	1.5610
Training Epoch	10.00	1000	10.00	1000	14.00	1000	8.00	1000
Training Time	00:00	00:28	00:00	00:27	00:00	00:30	00:00	00:29

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TABLE III. PREDICTION RESULT WITH MLP, RBF, VMF-MLP AND VMF-RBF AT LOS SITE-2

ANN Training	MLP		RBF		VMF-MLP		VMF-RBF	
Algorithms/Prediction Indices	trainlm	trainbr	trainlm	trainbr	Trainlm	trainbr	trainlm	trainbr
r	0.9580	0.9860	0.9790	0.9790	0.9810	0.9900	0.9840	0.9840
RMSE	3.9580	2.3740	2.7550	2.7550	2.6360	2.0670	2.3470	2.3470
MAE	2.5910	1.6670	2.2070	2.2070	1.9810	1.4900	1.9010	1.9010
SD	3.0110	1.5470	1.6460	1.6460	1.7500	1.3180	1.3760	1.3760
Training Epoch	10.00	1000	11.00	1000	13.00	1000	17.00	1000
Training Time	00:00	00:28	00:00	00:33	00:00	00:28	00:00	00:32

The fixed three-layered RBF network architecture ensures keeping network size as low as possible to ensure a reduction in transmission overhead and good generalization.

Training of the neural network model with BR algorithm for improved network generalization has a tradeoff of extra training time in comparison to the LM training algorithm, which trains the neural network models instantly with almost zero time and fewer training epoch. The results of applying VMF to the MLP and RBF ANN models for denoising to enhance better prediction of the signal power trend by removing the unwanted data in the form of noise are shown in Table I and Table III under VMF-MLP and VMF-RBF, respectively.

For NLOS of site-1, VMF-MLP gives *r* of *0.9600* compared to *0.9490* for VMF-RBF with the BR training algorithm. Vector median filter-MLP gives *2.1380*, *1.5000*, and *1.4510* for RMSE, MAE, and SD compared to *2.3550*, *1.5370*, and *1.5610* for VMF-RBF network. The same trend is seen for the LOS in site-2 where *r* for VMF-MLP is *0.9900*, RMSE is *2.0670*, MAE is *1.4900*, and SD is *1.3180* in comparison to VMF-RBF where r is *0.9840*, RMSE is *2.3470*, MAE is *1.9010*, and SD is *1.3760*. Fig. 4 and Fig. 5 show the spreading of the measurement data over distance for NLOS and LOS in site-1 and site-2, respectively, and predicting these measurement data using MLP, RBF, VMF-MLP, and VMF-RBF with LM and BR training algorithms. It is clearly shown that prediction of the measured data using VMF for both MLP-ANN and RBF-ANN give improved prediction result as shown in the figures with orange color, which dominates predictions with conventional MLP-ANN and RBF-ANN, respectively.

VI. CONCLUSIONS AND FUTURE RECOMMENDATIONS

Different signal power loss models have been utilized over the years to predict signal attenuation loss in cellular communication environments. These include conventional models such as Hata, Free Space, COST 234, etc. This research work designed and implemented an adaptive signal denoising technique using a vector median filter built on a multi-layer perceptron artificial neural network and radial basis function artificial neural network. The data denoising technique is employed in the removal of unwanted signal inform of noise in the measured data set before training with the neural network models. Comparative analysis of the performance of the designed adaptive models: VMF-MLP and VMF-RBF and the conventional MLP and RBF artificial neural networks were carried out. This was achieved using 1st order statistical indices, the RMSE, MAE, SD, and the coefficient of correlation. The prediction using the designed VMF-MLP and VMF-RBF neural networks demonstrate improved prediction accuracy in comparison to conventional MLP and RBF neural networks. This shows that data denoising through pre-processing enhances both training and prediction accuracy.

Future work will utilize other artificial neural network models, such as generalized regression network models built on vector median filters, to investigate their predictive ability compared to the conventional generalized regression network model without applying filtering techniques.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Virginia C. Ebhota (VCE) and Viranjay M. Srivastava (VMS) conducted this research; VCE designed 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.

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