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Improved Adaptive Signal Power Loss Prediction Using Combined Vector Statistics Based Smoothing and Neural Network Approach

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Abstract—Predicting signal power loss between the transmitter and receiver with minimal error is an important issue in telecommunication network planning and optimization process. In recent years, median order statistic filters have been exploited as a preprocessing constituent for analyzing signals. This work presents a resourceful predictive model, built on multi-layer perceptron (MLP) network with vector order statistic filter based preprocessing technique for improved prediction of measured signal power loss in a microcellular LTE network environment. The predictive model is termed Vector statistic filters multilayer perceptron (VSF-MLP). In terms of some essential performance evaluation indices such as the correlation coefficient, root-mean-square error and coefficient of efficiency, results show that VSF-MLP model prediction performs considerably better than the standard MLP model prediction approach on signal power data collected from different study locations in typical urban terrain.

1. INTRODUCTION

Propagation path loss is referred to as the unwanted loss in transmitted power density enroute the transmitter to the receiver in cellular radio communication channels. This loss arises due to environmental blockades and other multipath propagation effects in the radio communication channels, thus causing the received signal power to both fluctuates and attenuates around the user equipment (UE) terminals.

To estimate and predict the signal attenuation loss in any cellular radio communication environment for network planning and optimization purposes, path loss models are used. Some of the basic available conventional models in literature for the loss prediction includes, but not limited to the following: Free space, Lee, COST 234 Hata, Hata, Walficsh-Bertoni, Walficsh-Ikegami, dominant path and ITU models. But, due to poor prediction accuracy and lack of computational efficiency of these conventional models with propagated signal data in different cellular network environments [1–3], many researchers have shifted their focus to the domain of artificial neural networks (ANN) models.

ANN are widely recognized special computing tools and models that process information in similar manner like the brain. They are made of artificial neurons which can be trained to carry out some specific tasks. Thus, they have found useful applications in various academic disciplines like Accounting and Finance, Science and Engineering, Health and Medicine, etc. Specifically, neural networks have been widely used in literature for control systems [4], data stimulation [5], mining of hidden patterns [6–8], adaptive trend prediction and extraction of useful information from datasets/databases [9–14].

Different neural network architectures and models exist in literature, but the most popular one among them is the multi-layer perception (MLP), with attribute to its superb architecture and comparably clear algorithm [15]. Though standard MLP networks have been employed to model and predict different signal data, they suffer due to following fundamental drawbacks. First, conventional

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MLP networks perform poorly in handling noisy data [6–8]. Also, MLP networks lack capabilities in dealing with incoherence datasets which contracts with smoothness [8]. Moreover, conventional MLP networks cannot deal with complex and higher nonlinear dataset [8, 16].

Recently, attentions have been drawn to the area of data preprocessing in boosting the training efficacy and prediction deftness of neural network-based algorithms. Some of the key data preprocessing techniques include: sampling, which opts for a subset representation of a bulky datasets; normalization, which standardizes data for a better access; denoising, which succors in removing noise from datasets; transformation, which helps in manipulating raw datasets in order to produce a single input and among others.

In the area of data denoising, smoothing and transformation, different techniques such as match filtering, singular spectrum analysis, moving average smoothing, factor analysis, wavelet multi-resolution analysis, and among others, have been examined in some previous works [17–29].

Specifically, in [17–19], a combination of wavelet denoising method and neural network model was applied to trend prediction in rainfall time series dataset. The authors found that the combined wavelet neural network modeling based prediction is more efficient than using only the ANN models. The same approach was also used in [19] and [20], but for enhanced prediction of underground water levels and earthquake data respectively.

A study in [21] presented three data preprocessing approaches involving moving average (MA), filtering-based singular spectrum analysis (SSA) and principal component analysis (PCA) with modular neural networks for improved rainfall data predictions in China and Indian. In [22], the efficacy of dynamic filtering and convolution on accurate prediction of video and stereo data was proposed and demonstrated. In [23], a data preprocessing based modeling technique is applied to examine the daily reservoir inflow, and it discovered that model-driven prediction accuracy of the uneven inflow of the reservoir only improved when the preprocessed seasonal datasets were used. The authors in [24] explored the combination of dynamic linear model and Kalman filters to predict missing occurrences in time series sensor data stream, and they concluded that the application of the filter with linear model is a viable methodology for boosting the prediction efficiency of sensor data. A similar linear data filtering approach has been employed in [25], to analyze and predict cellular network coverage, but using CDMA2000 signal data.

The results and conclusion from the previous works above showed that the exploration of the information content in a datasets through preprocessing plays a major role in enhancing the model training and the prediction precision. However, the authors above only concentrated on time series datasets with linear smoothing-based data filtering and standardization approach which does not capture the stochastic nonlinearity in some multifaceted spatial datasets.

In this work, a combination of nonlinear data filtering-based denoising method and MLP neural network model is proposed for improved prediction of measured microcellular signal power dataset. The continuing part of this research work is structured in the following pattern: Section 2 contains a brief discussion of order statistics filters. In Section 3, the MLP concept, Levenberg-Marquardt and back propagation algorithms are concisely described. In Section 4, a description of the signal dataset used and study locations are presented. Sections 5 and 6 contain the neural network models used, their training pattern, results, discussion and performance evaluation criteria employed. The concluding part of the work is provided in Section 6.

2. METHODOLOGY

2.1. Order Statistics Filters

Noise is any undesirable information that contaminates desired signal. Every measured data or real signal measuring process contains some amount of noise which may have been added to the desired signal owing to thermal or natural environmental phenomena and other physical accouterments associated with the signal generation structure and data sampling process. Filtering in the utmost universal term, is a method of noise detection and extraction in dataset, in order to moderate the influence of errors on the succeeding input data analysis. It also helps to enhance or reveal the actual information about a particular quantity of interest in any given dataset.

Different filtering methods are presented in the literature for denoising signal data. Typically, the techniques can be group into two, namely, the linear filtering and nonlinear filtering. The performance of each filtering technique hinges on its ability to detect and remove the presence of noise from the desired signal data. Linear filters (e.g., mean filter, wiener filter, and Gaussian filter) are known to perform poorly in the presence of non-additive or non-Gaussian signal dependent noise [30, 31]. The concept of nonlinear filtering is centered on the theory of nonlinearity. Thus, our focus in this work is on nonlinear filters, particularly, vector order statistics filters. This work focuses on two nonlinear order statistics filters namely, vector median filters (VMF) and vector L filters (VLF), where L symbolizes the typical parameter.

2.1.1. Vector Median Filters (VMF)

The use of median filter was first proposed in 1974 by Tukey [32], as a time series-based data smoothing method. The VLF are robust ranked order filters for signal data smoothing and are well suitable when the noise sorts and characteristics are unknown [33, 34]. Given N observations of x_i, $i = 1, \dots, N$, the median x_{med}, of the dataset of x_i can be expressed by:

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

where, $f(x_{med}) \leq f(x_i) \vee x_i$, $x_{med} \in \{x_i, i = 1, \dots, N\}$ and x_i defines the k dimensional vectors $[x_i, x_{i2}, x_{i3}, \dots, x_{ik}]^T$.

2.1.2. Vector L Filters (VLF)

The VLF, which is a generalization of median filters, was first introduced in [35], utilizing combined linear Order Statistics. The covariance matrix with respect to the ordered samples is approximated using Taylor expansion [36]. It can be defined by:

$$Tn = \sum_{i=1}^{N} a_i x_i, \quad \text{where} \quad \sum_{i=1}^{N} a_i = 1 \tag{2}$$

with $a_i' s$ expressing the set of weights which describes the performance of the estimators.

2.2. Multilayer Perception Neural Networks

The MLP architecture or model is composed of distinctive networks of simple neurons which are designed in different layers as illustrated in Figure 1. The input data are transmitted through the layers in a forward direction shown in Figure 1 which is a single (i.e., one) hidden layer MLP neural network architecture, and the output can be expressed as:

$$y_i = f_o\left(\sum_{j=0}^{N} w_{jq}\left(f_h \sum_{i=0}^{N} w_{iq} x_i\right)\right) \quad \text{for} \quad q = 1, 2, \dots, N \tag{3}$$

where w_{iq} and w_{jq} indicate the respective connection weight and synaptic weight vectors in relation to the hidden layer neuron-inputs and from hidden layer-output neuron.

x_i stands for the input vector elements, $i = 1, \dots, N$.

f_o and f_h stand for the respective output layer and hidden layer activation function.

The MLP learning and training process entails minimizing the error function (i.e., cost function), which can be expressed as:

$$E(w) = \frac{1}{2} \sum (y_q - d_q) = \frac{1}{2} \sum_{q=1}^{N} e_q^2 \tag{4}$$

where $e_q = y_q - d_q$, with y_q and d_q indicating the desired target output value and the actual network value, respectively.

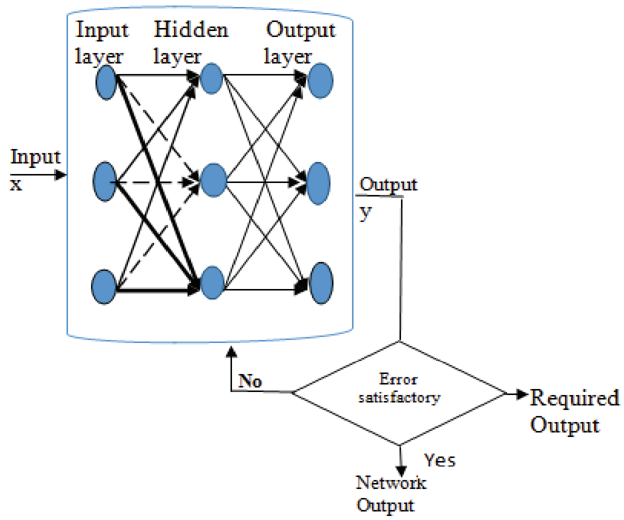

Figure 1. A one hidden layer MLP model.

2.3. Back Propagation (BP) Algorithm

The BP algorithm is one of the well-known neural network algorithms that employs the gradient descent method to minimize the cost function expressed in Eq. (3), and to accomplish this, we must have:

$$\Delta w = \frac{\partial E(w)}{\partial w_i} = 0 \tag{5}$$

The BP algorithm update rule is:

$$\Delta w = e(w) + \nabla \mathrm{w} \tag{6}$$

where:

$$\nabla w = -\eta \frac{\partial E}{\partial w} \tag{7}$$

and η designates the learning parameter.

2.4. Levenberg-Marquardt (LM) Algorithm

Another technique specially applied to minimize the error function problems is the LM algorithm [37], and it is adapted from Gauss-Newton and gradient descent methods. In correspondence to the cost function, Newton's method weight update is given as:

$$\Delta w = -\left[H(w)\right]^{-1} g(w) \tag{8}$$

where $g(w)$ and $H(w)$ denote the gradient vector and Hessian matrix expressed in Eqs. (9) and (10) respectively.

$$g(w) = J(w)^T e(w) \tag{9}$$

$$H(w) = J(w)^T J(w) + Q(w) \tag{10}$$

with $J(w)$ being the Jacobian matrix and

$$Q(w) = \sum_{i=1}^{N} \nabla^2 e(w) e(w)^T \tag{11}$$

Assuming that $S(w) = 0$ for the Gauss-Newton method, then, Eq. (8) with the gradient method would become:

$$\Delta w = -\left[J(w)^T J(w) + \mu I\right]^{-1} J^T(w) e(w) \tag{12}$$

The expression in Eq. (12) is the LM weight update, with I being the identity matrix and μ the damping parameter.

2.5. Combination of Vector Order Statistic Filters with MLP Network Model

The set-up of the proposed predictive model termed vector statistic filters multi-layer perceptron (VMF-MLP) is illustrated in Figure 2.

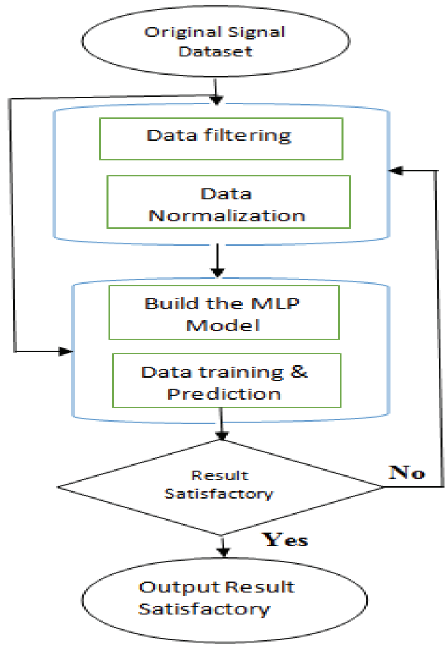

Figure 2. The proposed prediction approach based on combined vector order filtering and MLP neural architecture.

The prediction process is such that the measured signal power datasets are first preprocessed with order statistic filters, and then standardized, before feeding desired resultant output components to the MLP network model to enable it deliver training, testing and validation effectively.

2.6. Data Collection

The field test measurements were carried out around four operational Long term Evolution (LTE) cellular networks base station (BS) sites in Waterline areas of Port Harcourt City, with concentration on built-up busy urban streets, and roads. The Waterline is a typical urban area with a flat topography and mixed commercial and residential building edifices. As revealed in Table 1, the BS antenna heights range from 28 m to 45 m, elevated above the ground level to broadcast signals in three sectors configuration.

With the aid of drive test equipment which includes the Global Positioning System (GPS), HP Laptop, two Samsung Galaxy mobile Handsets (Model-SY 4) and network scanner, signal power measurements were conducted along different routes round the cell sites, in active mode. Specifically, drive tests around sites I, II and IV were performed via non-line of sight (NLOS) routes, while that of sight III was piloted through line of sight (LOS) route, such that there were no obstructions between the BS and user equipment termina. A snap shot of data collection in route I is revealed in Figure 3. All the test equipment were connected together with USB cables and housed in a Gulf car before the field drive test measurement. Also, both the Samsung handsets and the HP laptop were both enhanced with Telephone Mobile Software (TEMS, 15.1 version), which enable us to access, acquire and extract signal data including serving BS information after measurement. A total of 1,502 signal data points were extracted for further analysis using MapInfo and Microsoft Excel spreadsheet.

The measured signal power, called RSRP, is related to propagation path loss by:

$$RSRP(\text{dBm}) = P_{tx} - G_t - G_r - L_t - L_r + Pl \tag{13}$$

where: RSRP indicates Reference Signal Receive Power; Lr, Lt and Pl indicate the received feeder

Table 1. Measurement campaign parameters in LTE network.

	Site I	Site II	Site III	Site IV
Parameter	Value			
Operating Frequency (MHz)	2600	2600	2600	2600
BS Antenna Height (m)	28	30	45	32
BS antenna gain (dBi)	17.5	17.5	17.5	17.5
Transmit power (dB)	43	43	43	43
Feeder Loss (dB)	3	3	3	3
Transmitter cable loss (dB)	0.5	0.5	0.5	0.5
Mobile antenna height (dB)	1.5	1.5	1.5	1.5

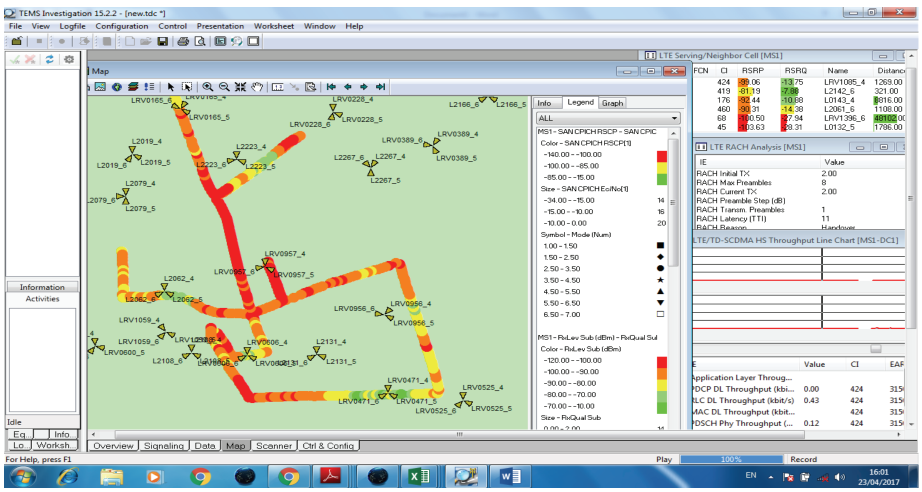

Figure 3. A snap shot of the drive test routes of the acquired RSRP data in site 1.

loss, transmitter loss and propagation path loss respectively. *Gr* and *Gt* stand for receiver gain and transmitter gain, while *Ptx* indicates the BS transmit power.

2.7. Neural Network Training with MLP, VMF-MLP and VLF-MLP Models

A 2013a MATLAB software platform was employed to implement the models. For optimal neural networks learning and training with the three investigated models, the measured signal dataset were shared into three subsets as follows: a training set (70% of the data), testing set (15% of the data) and validation set (15% of the data). The early stopping method was employed to cater for over-fitting during training. The training embroils the connection weights adjustments such that the network is able to predict the assigned value from the member training set. Levenberg–Marquardt training algorithm was utilized to ascertain the training capabilities of the investigated MLP, VMF-MLP and VLF-MLP schemes.

As the measured signal power data contain different values with different scales, adjusting and normalizing the dataset to improve the network training phase is very important. Thus, here, the vector normalization technique is considered and the normalizing equation is given by [32]:

$$x_v = \frac{x}{\sqrt{\sum_{l=1}^{n} (x_i)}} \tag{14}$$

where x_v and x_i indicate normalized and original data values respectively.

Also, to examine the prediction accuracy of each scheme, five statistical indices were utilized. The indices include: Coefficient of Efficiency-COE, correlation coefficient-R, standard deviation-STD, root mean squared error-RMSE, and mean absolute error-MAE. The five indices are defined in Eq. (15) to Eq. (19) as follows:

$$MAE = \frac{1}{N}\sum_{q=1}^{N}|y_q - d_q| \tag{15}$$

$$RMSE = \sqrt{MSE} = \frac{1}{N}\sqrt{\sum_{q=1}^{N}[y_q - d_q]^2} \tag{16}$$

$$STD = \sqrt{\left(\frac{1}{N}\sum_{q=1}^{N}|y_q - d_q| - MAE\right)^2} \tag{17}$$

$$R = \frac{\sum_{q=1}^{N}(y_q - \bar{y}_k)(y_q - \bar{d}_k)}{\sqrt{\left[\sum_{q=1}^{N}\left[(y_k - \bar{y}_k)^2\right]\right]\left[\sum_{q=1}^{N}\left[(y_k - \bar{d}_k)^2\right]\right]}} \tag{18}$$

$$COE = 1 - \frac{\sum_{q=1}^{N}[y_q - d_k]^2}{\sum_{k=1}^{Ktest}[y_q - \bar{y}_k]^2} \tag{19}$$

where y_q denotes the desired target output, d_q the actual network output, $\bar{y}_q$ the mean of the actual network output, and $q = 1, 2, \ldots, N$ are values the signal power sample.

3. RESULTS AND DISCUSSION

This part presents the results and discussion of the MLP, VMF-MLP and VLF-MLP network models employed to learn and predict the measured LTE signal power. Figures 4 to 7 show the measured signal power and their predictions in sites 1 to 4, using MLP, VLF-MLP and VMF-MLP models. Table 2 shows the summarized performance results of the three neural network models employed to predict the measured signal power, using MAE, RSME, STD, COE (%) and R indices. A closer value of R and COE (%) to 1 and 100, respectively, indicates better performance in predicting or fitting the actual data. On the other hand, the lower the values of MAE, STD and RMSE are, the better the neural network model prediction performance. From Table 2, it is established that VMF-MLP and VLF-MLP models attained the lowest MAE, RSME, STD values in the four study locations, compared to MLP model. Similarly, VMF-MLP and VLF-MLP models also attained the highest prediction accuracy in terms of R and COE, as compared to other models in the four study locations.

The spreading and distribution of the mean signal prediction error along the measurement routes using MLP, VLF-MLP and VMF-MLP models during the training, testing and validation period are presented in Figures 8 to 11. From the figures, minimum error spreads with VMF-MLP and VLF-MLP models along the measurement distance indicates superb signal prediction accuracy, compared to using standard MLP models. It is found from the plotted graphs that the prediction values from VLF-MLP and VMF-MLP models matched properly and better with the measured signal values, than MLP model prediction method.

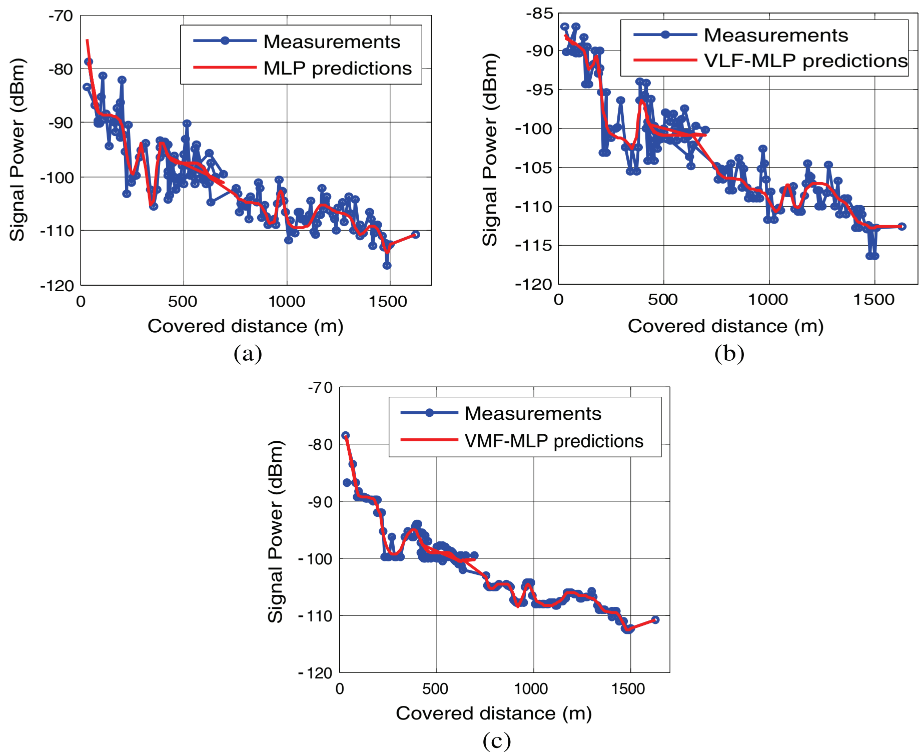

Figure 4. (a) MLP Model Signal predictions versus covered distance in site I. (b) VLF-MLP model Signal predictions versus covered distance in site I. (c) VMF-MLP model Signal predictions versus covered distance in site I.

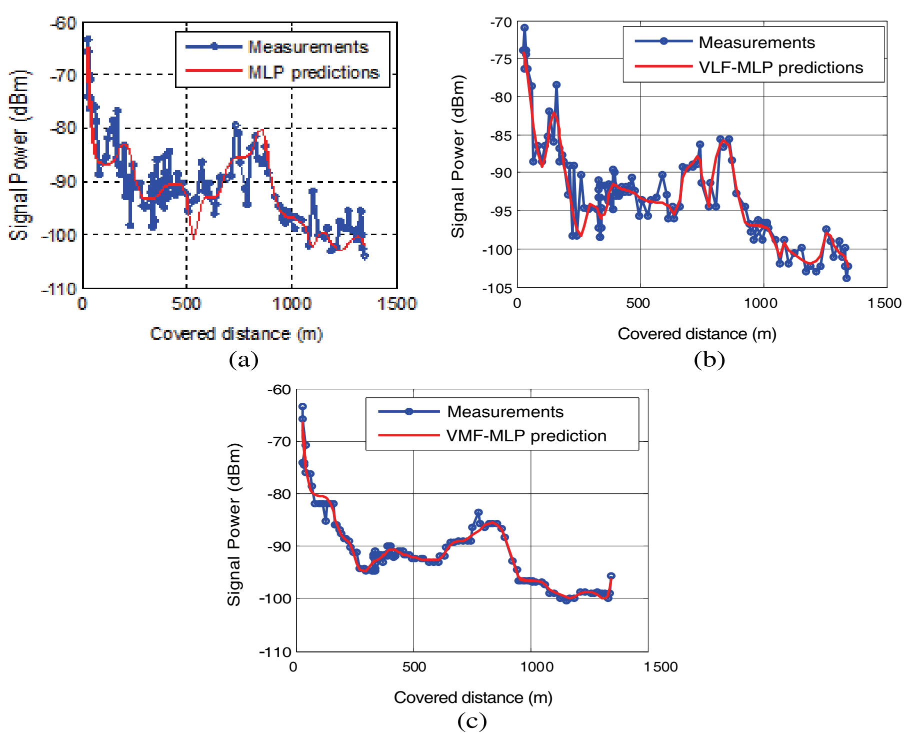

Figure 5. (a) MLP model Signal predictions versus covered distance in site II. (b) VLF-MLP model Signal predictions versus covered distance in site II. (c) VMF-MLP model Signal Predictions versus covered distance in site II.

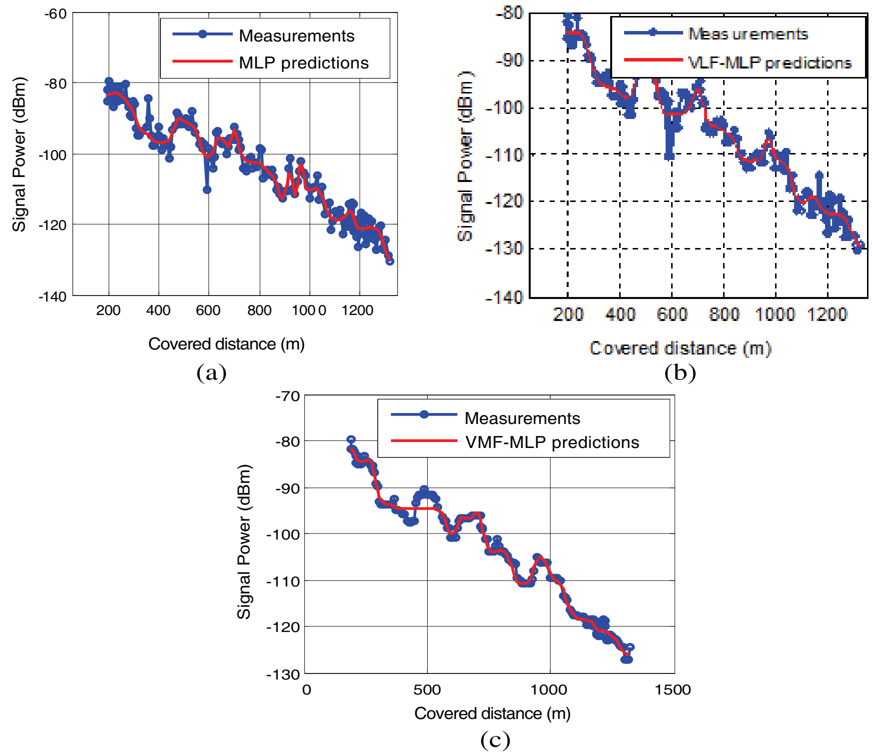

Figure 6. (a) MLP model Signal predictions versus covered distance in site III. (b) VLP-MLP model Signal predictions versus covered distance in site III. (c) VMF-MLP model Signal predictions versus covered distance in site III.

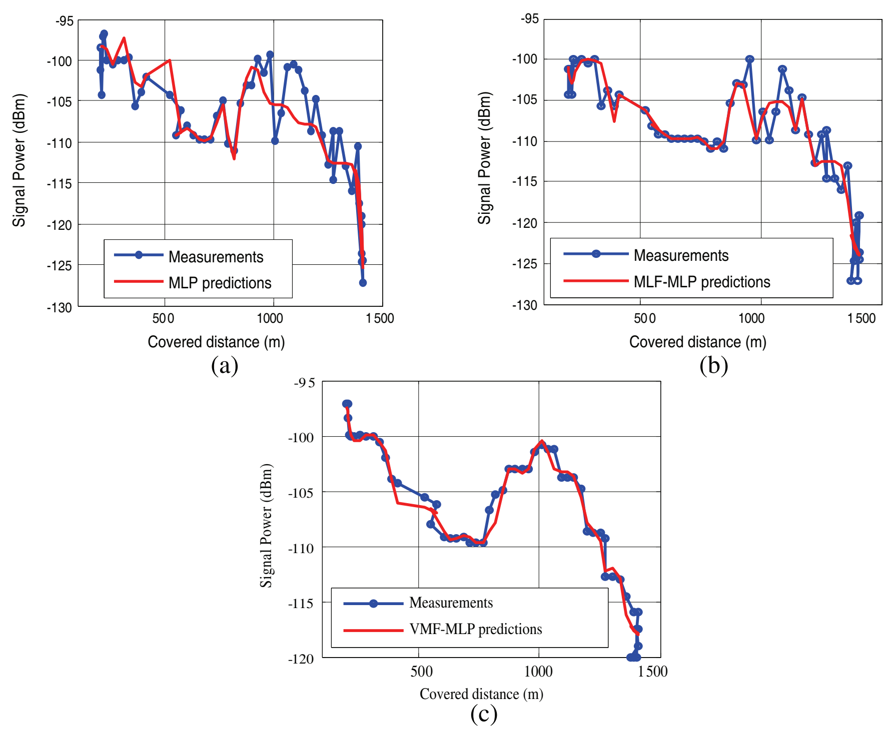

Figure 7. (a) MLP model Signal predictions versus covered distance in site IV. (b) MLP model Signal predictions with versus covered distance in site IV. (c) VMF-MLP model Signal predictions versus covered distance in site IV.

Table 2. Computed first order statistics with MAE, RSME, STD and R for sites 1 to IV.

	MLP Model Prediction				
Sites	MAE	RMSE	STD	R	COE (%)
I	2.071	2.777	1.849	0.931	86.83
II	1.992	2.529	1.557	0.982	96.49
III	2.677	2.642	2.642	0.872	76.16
IV	1.967	1.779	1.779	0.934	87.27
	VMF-MLP Model Prediction				
I	0.696	1.079	0.825	0.988	97.61
II	0.867	1.229	0.870	0.995	99.14
III	0.784	1.271	1.001	0.982	96.59
IV	0.734	1.071	0.780	0.986	97.24
	VLF-MLP Model Prediction				
I	1.464	1.947	1.284	0.957	91.64
II	1.587	2.129	1.459	0.987	97.42
III	1.663	2.285	1.567	0.941	88.62
IV	1.504	2.343	1.796	0.946	89.97

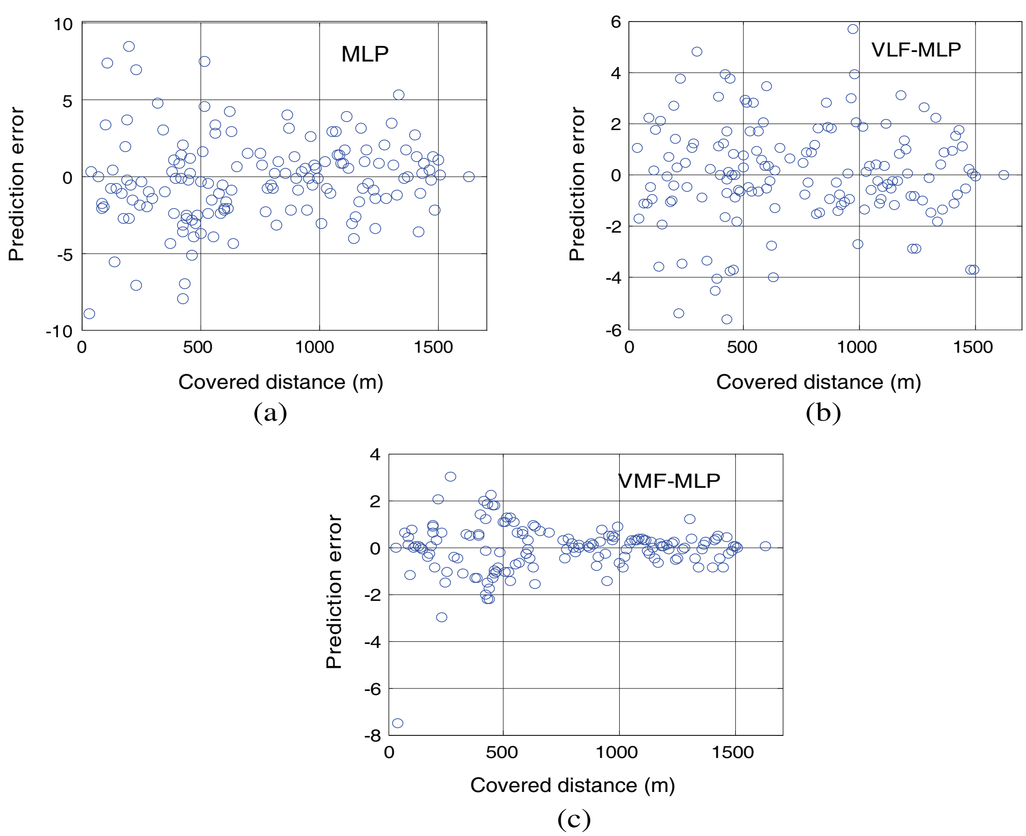

Figure 8. (a) Signal prediction error versus covered distance with MLP model, in site I. (b) Signal prediction error versus covered distance with VLF-MLP model in site I. (c) Signal prediction error versus covered distance with VMF-MLP model in site I.

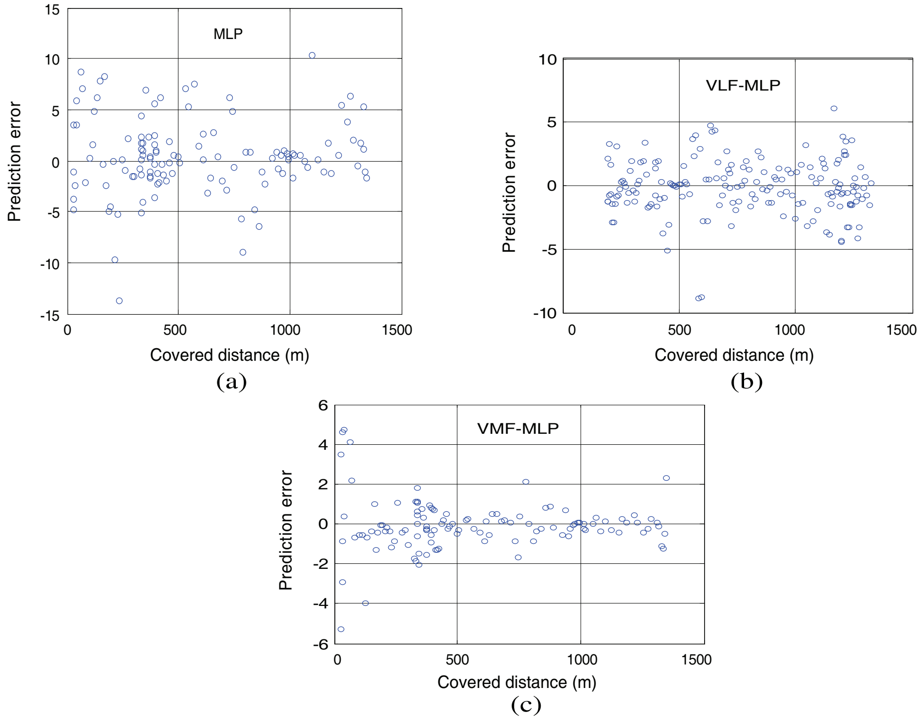

Figure 9. (a) Signal prediction error versus covered distance with MLP model in site II. (b) Signal prediction error versus covered distance with VLF-MLP model, in site II. (c) Signal prediction error versus covered distance with VMF-MLP model, in site II.

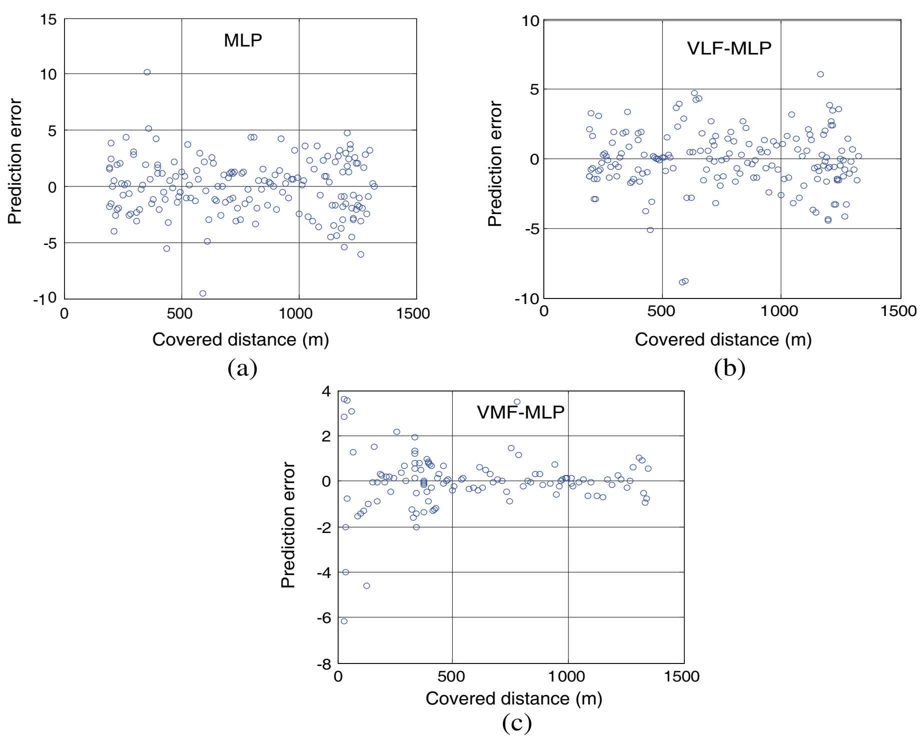

Figure 10. (a) Signal prediction error versus covered distance with MLP model, in site III. (b) Signal prediction error versus covered distance with VMF-MLP model in site III. (c) Signal prediction error versus covered distance with VMF-MLP model, in site III.

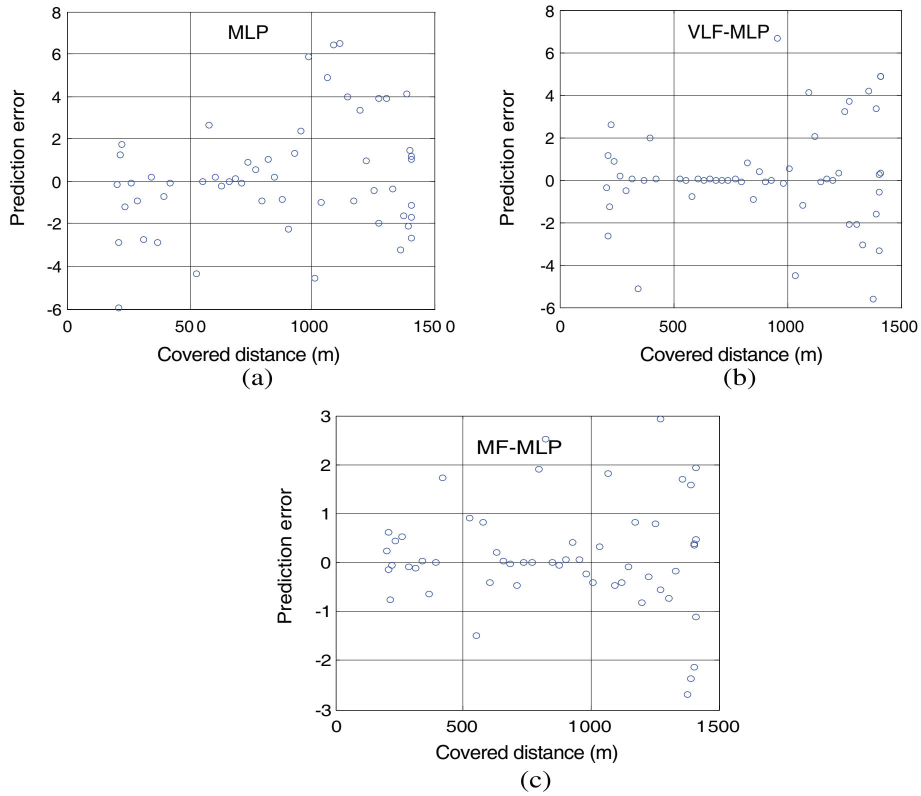

Figure 11. (a) Signal prediction error versus covered distance with MLP model, in site IV. (b) Signal prediction error versus covered distance with VLF-MLP model, in site IV. (c) Signal prediction error model versus covered distance with VMF-MLP, in site IV.

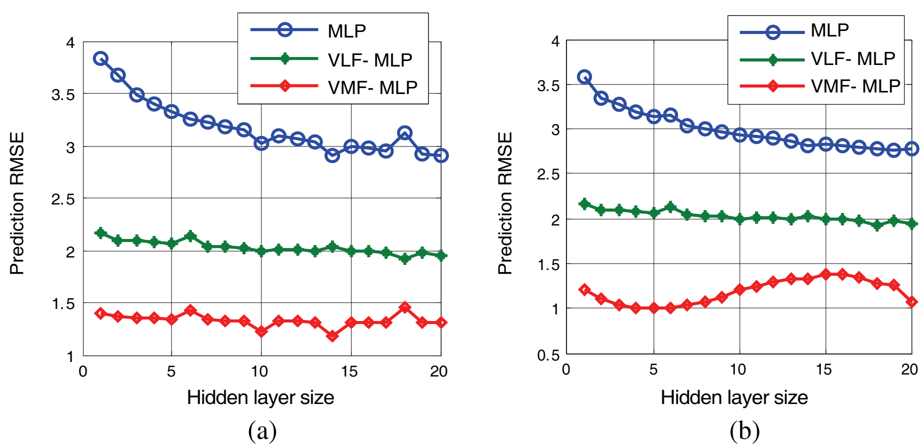

Figure 12. (a) Signal prediction RMSE error at different Hidden layer size using MLP model trained with GD algorithms, in site I. (b) Signal prediction RMSE error at different Hidden layer size using MLP model trained with LM algorithm, in site I.

Shown in Figures 12(a) and 12(b) are graphically presented results of the three investigated neural models trained with Levenberg-Marquardt (LM) and standard Gradient (GD) algorithms at varied hidden layer sizes for comparative study in site I. From the plotted graphs, it is plainly clear that the RMSE prediction errors of MLP, VLF-MLP and VMF-MLP models trained with LM algorithm are lower than the ones trained with GD algorithm. The superb prediction accuracy of the LM's algorithm can be ascribed to its high speed of convergence, though it requires more memory compared the GD algorithm.

4. CONCLUSION

To estimate and predict the signal attenuation loss in any cellular radio communication environment for network planning and optimization purposes, path loss models such as free space, Lee, COST 234 Hata, Hata, Walficsh-Bertoni, Walficsh-Ikegami, dominant path and ITU models are often used. But, due to poor prediction accuracy and lack of computational efficiency of these conventional models with propagated signal data in different cellular network environments, many researchers have shifted their focus to the domain of artificial neural networks (ANN) models. This is due to ANN model's high computation speed and capacity to learn input-output relationships of nonlinear complex systems and sceneries.

In this work, vector order statistics filters based preprocessing technique have been exploited to enhance adaptive trend prediction of stochastic noisy signal power data using ANN model. The proposed predictive approach is termed Vector statistic filters multi-layer perceptron (VMF-MLP). By means of different performance indices such as coefficient of efficiency, correlation coefficient, standard deviation, root mean squared error, and mean squared error, the adaptive prediction results on long term evolution signal power data collected from different study locations in urban terrain show that VMF-MLP model performs considerably better compared to standard MLP prediction approach. This rightly implies that the preprocessing of the information content in datasets enhances its training and prediction accuracy with neural network models.

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