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Analysis of the Strengths of Various Intermediate Layer Neurons of Radial Basis Function and Vanilla Neural Networks in the Prediction of Signal Power Loss Using Measurement Data from Micro-Cell Environment

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Abstract – *This work studied and compared the performances of VNN and RBF-NN models by variation of their individual intermediate layer neurons for effective prediction of electromagnetic signal power loss exerting measured data from micro-cell LTE environment. Their architectural structure, their individual characteristics and their training and prediction abilities in the prediction of signal power loss were studied and analyzed. Two different training techniques, the early stopping training technique and the Bayesian Regularization training technique were exerted for the training process and their performances compared. Results show superiority in the prediction of the measured dataset using 50 neurons in the intermediate layer of VNN and 70 neurons in the fixed intermediate layer of RBF-NN over all other various neuron number considered. Also, there is improved prediction using VNN over RBF-NN on application of Bayesian Regularization training technique and better performance using Bayesian Regularization training technique in comparison to early stopping training technique due to the ability of the Bayesian Regularization training technique to reduce both variance and bias during network training leading to improved generalization of the network. However, early stopping technique reduces variance but not bias. The VNN shows superior performance in the signal power loss prediction with the least RMSE, MAE, SD and highest r in comparison with the training results of RBF-NN model which requires more number of neurons in its fixed intermediate layer for more appropriate training. Also, training VNN requires lesser training time in comparison to training using RBF-NN model. The RBF-NN however shows good prediction performance in modeling of complex network. As the neuron numbers in the fixed intermediate layer get bigger, there prediction ability increases with better result output. Notwithstanding, training using RBF-NN requires more training time in comparison to training employing VNN.*

***Keywords**: Neural Networks, Neuron Variation Techniques, Bayesian Regularization Technique, Early Stopping Technique, Vanilla Neural Network, Radial Basis Function Neural Network, 1st Order Statistical Indices*

Nomenclature

ANN	Artificial Neural Network
AI	Artificial Intelligence
BP	Back Propagation
BS	Base Station
BR	Bayesian Regularization
GPS	Global Positioning System
GSM	Global System for Mobile communication
ITU-R	International Telecommunication Union-Radio
LOS	Line-of-Sight
LM	Levenberg-Marquardt
LTE	Long Term Evolution network
MATLAB	Matrix Laboratory
MSE	Mean Squared Error
NN	Neural Network
RF	Radio Frequency
T_X	Transmitter
R_X	Receiver
PL	Path Loss
RSRP	Reference Signal Receive Power
RMSE	Root Mean Square Error
RBF	Radial Basis Function
RSRP	Reference Signal Receive Power
SD	Standard Deviation
SSE	Sum of Squared Error
TEMS	Test Mobile System software
UHF	Ultra High Frequency
VNN	Vanilla Neural Network

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VHF	Very High Frequency
$W^{0}_{0,M}$	Bias weight of the output layer
W_{ij}^{N}	Weight value
δ	Weight update
α	Momentum parameter
η	Learning rate parameter
J	Jacobian Matrix
$J^{t}J$	Approximated Hessian
E	Error
λ	Damping factor

I. Introduction

Knowledge of unevenness of the field strength in the link is required in order to obtain the desired communication between the transmitter and the receiver [1]. This is very fundamental in the application that requires high quality signals such as broadcast network [1]. Careful planning and designs of the communication network has also become a necessity as a result of the emerging and advanced development of radio communication networks. A number of mechanism that affects the propagation of signals are mostly taken into consideration during VHF/ UHF network planning.

These mechanisms are diffraction over obstacles, free space attenuation, reflection from earth, etc. [2]. The propagation medium between the Transmitter (Tx) and the Receiver (Rx) remain a vital determining factor of the wireless radio communication network performance.

This is as a result of the dependent of the random nature of wireless radio channels on atmospheric variables such as pressure, temperature, atmospheric gases, humidity, etc. The field strength estimation at Very High Frequency (VHF) and Ultra High Frequency (UHF) bands is function of the effect of the refractive nature of the atmosphere as well as the transmitter and receiver locations [3]. The field strength actual and estimated value differences can be as a result of variation in the atmospheric conditions, with such variation capable of impacting the field strength negatively or positively for a considerable period. There might be long-term evolvement when the variation of the atmospheric radio refractive index gradient is pronounced from the normal propagation values [4]. It is therefore apposite to understand the effect of these mechanisms on radio wave signal during propagation [5]-[7]. Radio propagation models therefore, provides effective analytical techniques and predicts the strength of these signals in this regards [8]. Various models have been utilized over the years in the prediction of signal strength or signal power l during electromagnetic signal propagation. International Telecommunication Union-Radio (ITU-R) have developed and exerted various prediction models for field strength prediction on planning for point-to point area services. However, there are some limitations with their prediction models. For instance, recommendation P.528-3 [9] was assumed as a guide for prediction of Path Loss (PL) for the aeronautical mobile services applying frequency range of 125 MHz to 30 MHz with distance range of up to 1800 km. However, the curves generated were grounded on the obtained data mainly continental temperature climate. Thus, caution was assumed for its application on other climate. For the calculation of the received field strength over various paths, Recommendation P.526-12 [10] was derived by affording various models which are capable of differentiating obstacles and various path geometrics.

However, this Recommendation exerted only antenna heights and the range between Tx and Rx for the prediction of PL. There are other popular ITU-R model such as the Recommendation P.1546-5 [11] that provides techniques of field strength predictions for terrestrial services for broadcast, maritime mobile, land mobile and other fixed services that operates between 30 MHz and 300 MHz. These models exert interpolation and extrapolation of the transmitting and the receiving antenna heights, the distance, operating frequency, terrain clearance angle, relevant percentage of time, etc.

However, in common with all ITU-R models, there is no understanding of the intervening atmospheric conditions between transmitter and receiver. This work employs Artificial Neural Network (ANN) referred in this work as Neural Network (NN) models for the prediction and computation of signal power loss during electromagnetic signal propagation using measured data collected via a drive test from Long Term Evolution (LTE) micro-cell built-up environment. Considering the significance of finding the accurate propagation characteristics for various localities, the knowledge of signal propagation mechanism earlier mentioned was utilized in the collection of the measured data. Programs are written using the collected data and NN models employed for simulations to determine their performances at the variant of link distance between Tx and Rx as the signal propagates. In this paper, the performances of two traditional NN models, the Radial Basis Function Neural Network (RBF-NN) model and the Vanilla Neural Network (VNN) model in the prediction of loss of signal power during electromagnetic signal transmission are examined. While VNN architectural network comprises of an input and an output layers with one or more intermediate layers, the RBF-NN comprises of fixed three layer architectures [12]. The input layer of the RBF-NN has predictor variables with separate neuron for every variable. The fixed intermediate layer has various numbers of neurons while the output layer carries out the linear division. The network inputs are supplied by the input layer and the input datasets are re-mapped in the intermediate layer to ensure they are linearly divisible while it is then handed over to the output layer [13]. The RBF-NN is uniquely designed with architectural network that enables proper finding of the network size, initial parameters finding and adequate network training. There is presence of RBF centered at a point at every of the intermediate layer neurons which depends on the input-output predictor variables dimensionality [12], [14].

Additionally, every of the RBF-NN neuron has weight values which are thereafter handed over to the output network. The VNNs on the other hand are feed-forward architectural network that employ back propagation training techniques [15]. The weighted inputs and biases of the input layer is fed to the intermediate layer via a transfer function and then to the output layer [16], [17].

The VNN may have one or more intermediate layer network unlike the RBF-NN that has a one fixed intermediate layer architectural network. On selection of the right neuron numbers, and right activation function, the VNNs have shown to estimate efficient and measurable function between input and output vectors [18]. The VNN learns via repeated training of dataset exerting back-propagation algorithm. This research work examines individual performances of various neurons of fixed intermediate-layer RBF-NN and single-intermediate layer VNN for electromagnetic signal power loss prediction exerting measured dataset gotten from LTE micro-cell built-up area. Various training techniques were exerted during the NN models training, such as application of neuron variation while exerting early stopping and Bayesian Regularization approach for enhanced network training. Based on the overall result outputs, inferences are made for the best NN model to be utilize in solving practical problems such as electromagnetic signal power loss prediction.

The remaining part of the research work is organized as follows. Section II is background study which addresses the architectural structures of the RBF-NN and the single-intermediate layer VNN models. Section III explains the data collection procedure, Section IV states the performance metrics exerted for the NN training result analysis, while Section V is the training result analysis from trained RBF-NN and the single intermediate layer VNN. Section VI is the conclusion with the research findings and future research work

II. Background Study

This section studies the architectural structure of the RBF-NN and the single-intermediate layer VNN which are exerted in this work for signal power loss forecast using measured dataset.

II.1. Architectural Composition of the Fixed-Intermediate Layer Radial Basis Function Neural Network Model

Radial basis function neural network is in general three fixed architectural layered network as show in Fig. 1. The RBF-NN architectural structure are made up of fixed three-layers, the input layer that has one or more predictor variables with every of the variable associated with a separate neuron, a fixed intermediate layer that has various numbers of neurons and an output layer. Each of the neuron of the intermediate layer has a radial basis function that is centered at the point which depends on the dimension of input-output predictor variables.

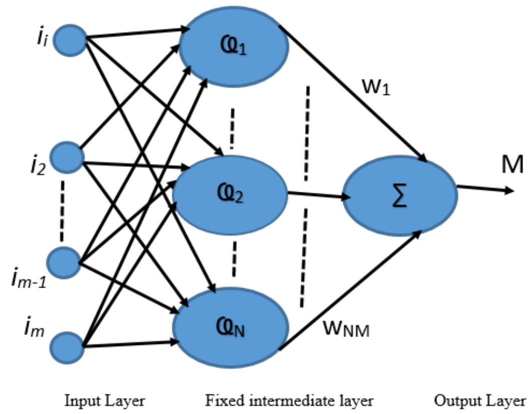

Fig. 1. Architectural composition of Radial Basis Function Neural Network Model (adapted from V.C Ebhota et.al. 2018)

The data sample to be trained is supplied to the RBF-NN via the input layer, these data are re-mapped by the fixed intermediate layer to make certain they are linearly divisible while the linear division is carried out at the output layer. The RBF-NN architectural structure ensure proper finding of the network size for the training dataset, finding proper initial training parameters and appropriate network training [19], [20], [23], [24]. Every neuron of RBF-NN has a weight w, which is multiplied by the values of the fixed intermediate layer while the summation sums the weighted values and subsequently transmits it to the output network. There is a RBF centered at the point for every of the intermediate layer which depends on the dimension of the input-output predictor variables [6], [21]. Each of the intermediate layer neuron has a RBF centered at the point. This depends on the dimensionality of the input-output predictor variables [6]. For input to the intermediate unit-N, the weighted by input vector a of the input weight w^h is [22]:

$$S_N = \left[i_1 w_{1,N}^h, i_2 w_{2,N}{}^h, \ldots, i_{m-1} w_{m-1,N-1}^h, i_m w_{m,N}^h \right] \quad (1)$$

where m is the index unit and N is the intermediate unit, i_m is m^{th} input and the $w_{m,N}^h$ is weight of input between m and N intermediate-unit. Output of intermediate unit is expressed as:

$$\varphi_N \left(S_N = \exp\left[\frac{\| S_N | - C_N \|^2}{\sigma_N} \right] \right) \quad (2)$$

φ_N is the intermediate unit N activation function, which normally is selected as Gaussian function, C_N is center of the intermediate unit N and σ_N is width of intermediate unit N. The output unit index (M) is expressed as:

$$O_M = \sum_{n=1}^{N} \varphi_N \left(S_N \right) W_{N,M}^0 + W_{0,M}^0 \quad (3)$$

$W_{N,M}^{0}$ is output weight between the intermediate layer and the output layer, and $W_{0,M}^{0}$ is bias weight of the output layer.

II.2. Architectural Structure of a Single-Intermediate layer Vanilla Neural Network Model

Vanilla neural network model has two major components which are the processing units also known as the neurons and the connections that connect the individual neurons known as the weight. The neuron is defined by the activation function when it receives an input [19], [20]. The activation function i.e. the transformation is expressed as:

$$f\left(j_N\right) = \frac{1}{1+\exp^{-jN}} \tag{4}$$

The net computation of the VNN is given as:

$$j_N = \sum_{i=0}^{N} W_{ij}^{N} i_N \tag{5}$$

N_i is inputs i index, W is the weight and j is the output of the intermediate layer. W_{ij}^{N} is weight value. The output computation is expressed as:

$$y_M = \sum_{j=0}^{N} W_{jy}^{N} j_N \tag{6}$$

The neuron output is y_M, the weight value is W_{jy}^{N} and i_o and j_o are the bias values. For more inter-connected intermediate layers of the VNN, the computatin of Equation (5) and Equation (6) remains the same for each of the neuron, except that the output of the neurons is for all time provided by the network inputs or the neurons outputs from the preceding hidde layer.

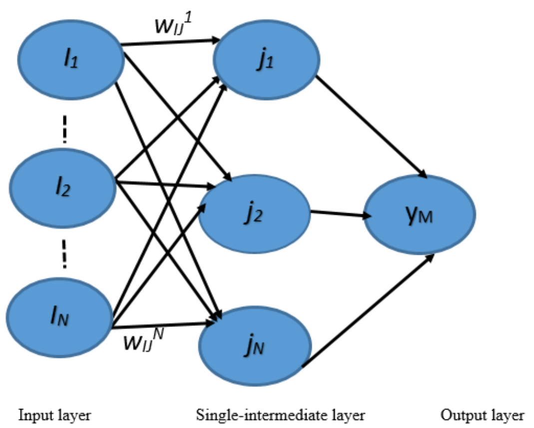

Fig. 2. Architectural Structure of Single-intermediate layer Vanilla Neural Network Model (adapted from V.C Ebhota et.al. 2018)

II.3. Characteristics of the Fixed-Intermediate Layer RBF-NN and the Single-Intermediate Layer VNN Models

The individual characteristics of the RBF-NN and the VNN such as the effect of their architectural structure and their ability to genrealize during network training for effective prediction of signal losses during elecromagnetic transmission are discussed.

II.3.1. The Fixed-Intermediate Layer RBF-NN and the Single-Intermediate Layer VNN Generalization Ablity During Network Training

The RBF-NN as well as the VNN has the ability to generalize during network training. Its weight convergence ability at a point for proper operation on datasets is known as gneralization [19]. The network configuration, the training instances and the problem complexity mostly define the proficiency of the network to generalize. The network architectural structure and the network training set size also add to the generalization ability of the network. The network architectural composition is expected to be in synchronization with the underlying physical complexity of the problem intended to be solved to ensure right impact on the training procedure. Keeping the size of the network as low as possible is however required for reduction in transmission overhead, thus, in view of the size of the training-set, the number of neurons for reaization of the training data has to correspond to the training instances as an over-sized network results to rise in data memorization leading to poor network generalization.

Datasets may overlearns during training of the NN leading to poor generalization of the network [20].

However, this can be avoided through different training methods such as exerting early stopping training method, exerting Bayesian Regularization (BR) training technique and rightful selection of fitting neuron numbers in the intermediate layer [16].

II.3.2. The Architectural Structure of the Fixed-Intermediate Layer RBF-NN and the Single-Intermediate Layer VNN

The VNN is a backpropagation algorithm that has its weighted data propagates by neuron inputs and bias randomly selected at the intermediate layer [20]. The net sum which is the overall VNN training output is determined at the intermediate nodes which results to an output response by application of a transfer function.

Possession of non-linear processing element and non-linear activation function are major characteristics of VNN. Sigmoid activation function which can either be hyperbolic tangent or logistic tangent is the activation function widely applied in VNN. The activation function at the output is transformeed as:

$$\phi\left(y_M\right) = \tanh y_M \tag{7}$$

Equation (7) could be a hyperbolic tangent when varied from -1 to +1 and a logistic function when varied from 0 to +1. The output of the the j^{th} neurons is the Y_M.

The training of the VNN is by error correction where an instantaneous error e_{j1}^N is defined from the system reaction at the processing element iteration J_I^N and d_{j1}^N as expected reaction for particular input:

$$e_{j1}^N = d_{j1}^N - j_1^N \tag{8}$$

The overall VNN weight by applying gradient descent theory can be adjusted by correction of current weight value by a term relative to current input and weight error [22]. This is expressed as:

$$w_{jy+1}^N = w_{jy1}^N + \eta\delta_{j1}^N y_m + \alpha\left(w_{jy}^N - w_{jy1}^{N-1}\right) \tag{9}$$

δ_{j1} is local error, α is the momentum parameter and η is learning rate parameter. The RBF-NN architecture is a feedforward multi-layer network majorly employ for multi-dimensional space interpolation. The feedforward of RBF-NN network involves neurons organization in layers [22]. The input data is transformed from the input space by use of a non linear activation function to intermediate space in intermediate layer. The euclidean distance between the input space and center of that unit is computed by the activation function argument of all the intermediate unit. As a result of non-linear estimation property of RBF-NN, they possess the ability to effectively model complex mapping which the perceptron neural networks can only model by having intermediary layers [8].

II.3.3. The Single-Intermediate Layer VNN and the Fixed-Intermediate Layer RBF-NN Learning Exerting Bayesian Regularization Training Technique

Bayesian Regularization (BR) algorithm has been exerted by the authors in this work in agreement with the Levenberg-Marquardt (LM) optimization [20]. The BR training algorithm ascertains the rightful arrangeemt that will give an appropriate generalized network by linear permutation of squared error and weight variables minimization. Both the VNN and the RBF-NN adopts the BR algorithm in adjusting the linear arrangment to guarantee a good generalized network at the end of the network training. The BR algorithm works with LM algorithm exerting the Jacobian for computation.

Nevertheless, the Jacobian assumes a performance which is sum of squared errors, thus, the network training carried out using BR algorithm ought to adopt Mean Squared Error (MSE) or Sum of Squared Error (SSE) performance function. The computation of Jacobian is done by the application of backpropagation and every of its variables which are modlified in agreement witth LM algorithm function approxiamtion method as shown below:

$$\left(J^t J + \lambda I\right)\delta = J^t E \tag{10}$$

J^tJ is approximated Hessian, δ is unknown weight update vector, E is error, λ is damping factor of Levenberg, J is Jacobian matrix. The damping factor is modified at all iteration for process optimization.

III. Data Collection Procedure, the Two Neural Network Models Training and Prediction

The field data were collected from a LTE network microcell environment via a Drive test. The dataset were collected from a Line of Sight (LOS) Base Station (BS) operating at 1900 MHz frequency band and BS antenna height of 40 m. The Derive test was carried out employing suitable equipment such as Laptop augmented with Telephone Mobile Network (TEMS 1.5.1 version), Global Positioning System (GPS), Network scanner, mobile phone augmented with TEMS software, other required accessories. A total of 2300 signal power points were extracted for analysis and Map Info and Microsoft Excel Spread sheet were employed for data extraction and standardization respectively. The signal power measured which is represented as Reference Signal Receive Power (RSRP) is related to Pl by:

$$P_{tx} - G_t - G_r - L_t - L_r + Pl \tag{11}$$

G_t is Tx gain, G_r is Rx gain, L_t is Rx feeder loss, L_r is Tx loss, Pl is path loss, P_{tx} is BS Tx power. The training of the single-intermediate layer VNN and the fixed-intermediate layer RBF-NN were trained using 2300 measured dataset. The data capturing was carried out in a way that appropriate measurement points covering different signal propagation conditions such as refraction, diffraction, reflection and scattering etc. Artificial Neural Network, ANN toolbox in MATLAB 2022b were exerted for the dataset training using BR mathematical training algorithm. The training was carried out adopting neuron variation and early stopping technique during training in the ratio of 70%:15%:15% for dataset training, testing and validation respectively. The neurons variation in the intermediate layers of the single-intermediate layer VNN and fixed-intermediate layer RBF-NN were varied in tens up to 70 neurons. Also, BR training approach was applied where 90% of the datasets were exerted for training and 10% exerted for dataset validation. Training the neural network models with the dataset was done for an average of ten runs while averaging the output result for better assessment. This also helps to ensure learning of the patterns from the dataset by the NN models for effective development of predictive ability. The results output for error analysis from the three different approaches adopted for the VNN and RBF-NN training i.e. the early stopping technique, the neuron variation method and the Bayesian Regularization method were established, computed and compared using 1st order statistical performance metrics.

IV. Performance Metrics

Four performance merics: the Root Mean Square Error (*RMSE*), the Mean Absolute Error (*MAE*), Standard Deviation (SD) and Correlation Coefficient (*r*) are exerted for result analysis. The *RMSE* measures the differnce between the actual output and the desired output [19]. It is expressed as:

$$RMSE = \sqrt{\frac{1}{N_{\exp}} \sum_{d=1}^{N_{\exp}} \left[l(d) - y_0(d) \right]^2} \tag{12}$$

The *MAE* calculates the closeness of the actual output to the desired output [20]. This is expressed as:

$$MAE = \frac{1}{N_{\exp}} \sum_{d=1}^{N_{\exp}} \left[l(d) - y_0(d) \right] \tag{13}$$

The *SD* is a measure of variation extent between the actual output and desired output. Small *SD* indicates data points closeness while huge *SD* indicates the reverse [21]. This is expressed as:

$$SD = \sqrt{\frac{1}{N_{\exp}} \left(\sum_{d=1}^{N_{\exp}} | l_d - y_d | - \mathrm{MAE} \right)^2} \tag{14}$$

The *r* measures relationship between the actual output and the desired output. It returns value between -1 and +1. The +1 indicates strong positive connection between the actual output and the desired output while -1 indicates a negative connection [22]:

$$r = \frac{N_{\exp} \sum l(p) - y_0(p) - \left(\sum l(p) \left(\sum y_0 \right) \right)}{\left(\begin{array}{l} \sqrt{N_{\exp} \left(\sum l(p) \right)^2} + \\ -\left(\sum l(p) \right)^2 \sqrt{N_{\exp} \left(\sum y_0(p) \right)^2} \end{array} \right)} \tag{15}$$

N_{exp} is measured experimental data number, $l(p)$ is measured signal power loss values, p^{th} is input pattern, and $y_o(p)$ is NN output.

V. Results Analysis from the VNN and RBF Training

The tables show the results of the fixed- intermediate layer RBF-NN and single-intermediate layer VNN training on variation of the neuron numbers in the intermediate layers and on application of two training techniques; the early stopping training technique and the BR training technique. 1st order statistical indices are exerted for results analysis. Table I and Table II show the effect of neuron number variation of the intermediate layer of a single-intermediate layer VNN and the fixed-intermediate layer of RBF-NN with 1st order statistical indices, the *RMSE*, the *MAE*, the *SD* and the *r* exerted in the analysis of the overall results from the training, testing and validation. The best prediction results while considering variation of neuron numbers in the VNN single-intermediate layer and RBF-NN fixed-intermediate layer are highlighted in green color.

Thereafter, the best results highlighted with green colors from training exerting fixed-intermediate layer RBF-NN and single-intermediate layer VNN while varying their intermediate layer neurons were re-trained using two training techniques: the early stopping training technique and the BR training technique. Training the fixed-intermediate layer RBF-NN and the single-intermediate layer VNN networks exerting early stopping techniques and BR technique, the overall results from the training, testing and validation of the networks are shown in Table III while Table IV respectively. The single-intermediate layer VNN and the single-fixed-intermediate layer RBF-NN were further trained using early stopping training technique and BR training technique as shown in Table III and Table IV respectively. The best results from neuron variation exerting the single-intermediate layer VNN were achieved when the network was trained with 50 neurons in the intermediate layer. It shows the least *MAE*, *RMSE*, the *SD* and highest *r*.

On application of other numbers of neurons in the intermediate layer varying from 10 to 70 neurons, there was either inability of the neural network model to adequately generalize and predict the measured dataset or to over-train the measured data.

TABLE I
TRAINING RESULTS FOR NEURON VARIATION
IN VNN SINGLE-INTERMEDIATE LAYER

Statistical Parameters For Comparison	Varied VNN Single-Intermediate Layer Neurons Trained With Br Algorithm						
	10 (neurons)	20 (neurons)	30 (neurons)	40 (neurons)	50 (neurons)	60 (neurons)	70 (neurons)
RMSE	2.9100	2.6840	2.5530	2.2350	1.8340	2.1650	2.4600
MAE	2.5650	2.4760	2.1050	1.9840	1.6640	1.6880	1.9410
SD	1.8930	1.8210	1.6400	1.3240	1.2110	1.4320	1.6980
r	0.8790	0.8990	0.9240	0.9790	0.9910	0.9060	0.9000
Training time(s)	00:00:05	00:0010	00:00:13	00:00:15	00:00:18	00:00:23	00:00:24

TABLE II
TRAINING RESULTS FOR NEURON VARIATION IN RBF-NN FIXED INTERMEDIATE LAYER

Statistical Parameters For Comparison	Varied RBF-NN Fixed-Intermediate Layer Neurons Trained With Br Algorithm						
	10 (neurons)	20 (neurons)	30 (neurons)	40 (neurons)	50 (neurons)	60 (neurons)	70 (neurons)
RMSE	6.8950	5.9900	5.2600	4.3640	2.9040	2.1980	1.7940
MAE	5.4040	4.6404	4.4440	3.7900	2.6660	1.8950	1.4240
SD	5.0100	4.8780	2.3100	1.9800	1.9100	1.7900	1.4860
r	0.7600	0.7990	0.8340	0.8901	0.9210	0.9620	0.9890
Training time(s)	00:00:12	00:00:18	00:00:29	00:00:34	00:00:41	00:00:44	00:00:47

TABLE III
COMPARATIVE ANALYSIS OF THE SINGLE-INTERMEDIATE LAYER VNN AND FIXED-INTERMEDIATE LAYER RBF-NN TRAINING USING EARLY STOPPING TECHNIQUE FOR IMPROVED NETWORK TRAINING

Statistical parameters for comparison	Number of intermediate layer neurons with best prediction	
	VNN (50 neurons)	RBF-NN (70 neurons)
Training time	00:00:18	00:00:47
RMSE	1.8340	1.7940
MAE	1.6640	1.4240
SD	1.2110	1.4860
r	0.9910	0.9890

TABLE IV
COMPARATIVE ANALYSIS OF THE SINGLE-INTERMEDIATE LAYER VNN AND FIXED-INTERMEDIATE LAYER RBF-NN TRAINING USING BAYESIAN REGULARIZATION TECHNIQUE FOR IMPROVED NETWORK TRAINING

Statistical parameters for comparison	Number of intermediate layer neurons with best prediction	
	VNN (50 neurons)	RBF-NN (70 neurons)
Training time	00:00:14	00:00:27
RMSE	I.7790	1.7530
MAE	1.6000	1.4110
SD	1.1210	1.3440
r	0.9992	0.9900

Figures 3 and 4 describe the simulation results of the prediction abilities of the single-intermediate layer VNN for network training showing the worst trained network with 10 neurons in the VNN single-intermediate layer and the best trained network with 50 neurons in the VNN single-intermediate layer respectively. The training results shows that training the single-intermediate VNN network with fewer neurons such as 10 neurons in the intermediate layer result to poor network generalization, thus very poor prediction of the measured dataset as can be seen in Figure 3.

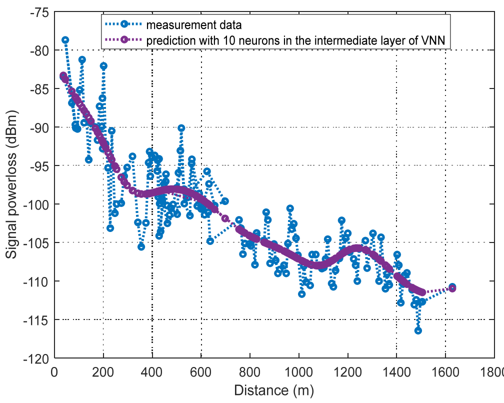

Fig. 3. Worst training prediction result exerting 10 neurons in the single-intermediate layer of the VNN

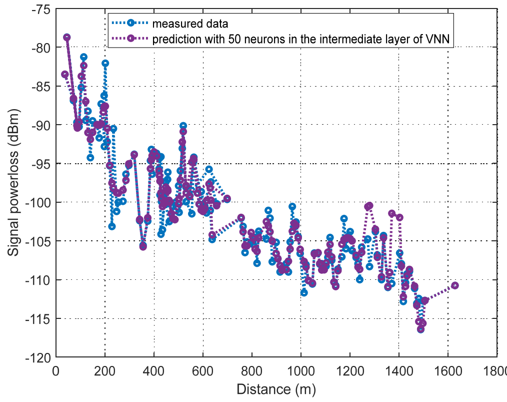

Fig. 4. Best training prediction result exerrting 50 neuron in the single-intermediate layer of the VNN

Figure 4 shows the best prediction result of the VNN exerting 50 neurons in the VNN single-intermediate layer capturing almost all the measured data. The prediction abilities of the 10 and 50 single-intermediate layer neurons of VNN in Figures 3 and 4 can clearly be observed from the figures. On appliction of 10 neurons in the intermediate layer, the measured dataset represented with blue dots couldn't be predicted by the single-intermediate layer VNN represented with purple dots while on application of 50 neurons in the intermediate layer of single-intermediate layer VNN, there are even prediction of the measured dataset by the single-intermediate layer VNN as can be seen in Figure 4.

Application of other numbers of neurons as considered and results shown in Table I and Table II either shows inabilty to predict the measured dataset or over-fitting during prediction of the measured dataset. Training results of fixed-intermediate layer RBF-NN model are shown in Table II and Figure 6 shows the best prediction of the measured dataset using the fixed-intermediate layer RBF-NN with 70 neurons in the intermediate layer.

As the network gets complex with increase in the intermediate layer neurons from 10 to 70, there is increase in the prediction ability of the network in comparison to training the neural network with lesser neurons in the intermediate layer of the RBF-NN such as training using 10 neurons in the intermediate layer.

However, increase of the neurons above 70 neurons in the intermediate layer results to over-fitting of the training network. 70 neurons in the fixed- intermediate layer of the RBF-NN gives the least *RMSE*. *MAE*, *SD* and the *r* while the worst results is seen training the RBF-NN with 10 neurons in the intermediate layer which gives very high *RMSE*, *MAE*, *SD* and very low *r*.

Graphical results from training the RBF-NN with 10 neurons and 70 neurons in their various fixed-intermediate layer are shown in Figures 5 and 6 respectively. From Figures 5 and 6 respectively, it can clearly been seen the difference in the training and prediction results of the fixed-intermediate layer RBF-NN on application of 10 neurons in the intermediate layer as shown in Figure 5 and 70 neurons in the intermediate layer as shown in Figure 6. There is over-fitting by the predicted RBF-NN represented by purple dots over the measured dataset represented by blue dots in Figure 5. This is as a result of insufficient neurons in the fixed-intermediate layer of the RBF-NN to sufficiently learn the pattern of the signal power loss of the measured dataset. However, as the training neurons in the intermediate layer increases, there is improvement on the prediction ability of the RBF-NN and on training the fixed-intermediate layer RBF-NN with 70 neurons in the intermediate layer, the result of training using 70 neurons in the intermediate layer shows an even prediction of the measured dataset by the prediction RBF-NN as seen in Figure 6.

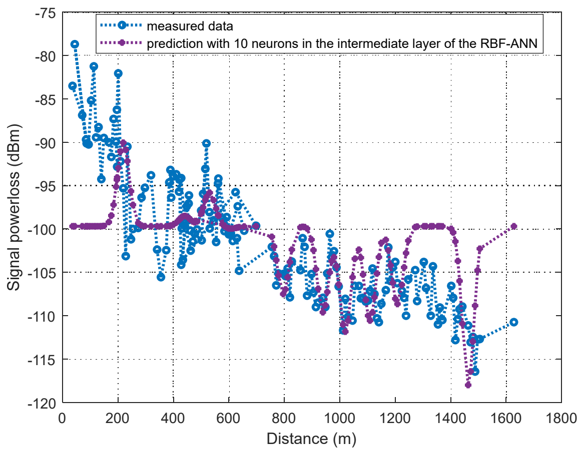

Fig. 5. Worst training prediction result exerting 10 neuron in the fixed-intermediate layer of the RBF-NN

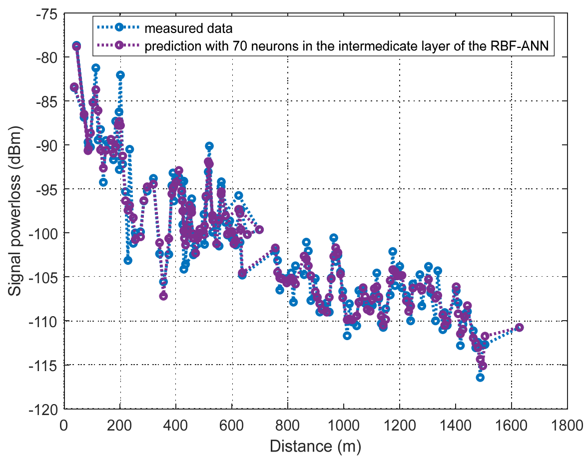

Fig. 6. Best training prediction result exerting 70 neuron in the fixed-intrmediate layer of the RBF-NN

Also considered in this work is a comparative analysis of the results of the best trained single-intermediate layer VNN and fixed-intermediate layer RBF-NN using two training techniques: early stopping technique and BR training technique. The results from both training techniques on re-training the single-intermediate layer VNN with 50 neurons in the intermediate layer and re-training the fixed-intermediate layer RBF-NN with 70 neurons in the intermediate layer give the prediction results shown in Table III and Table IV respectively.

Bayesian Regularization training techniques gives the best training results due to its ability to reduce both bias and variance during network training which results in reduction of poor network generalization by taking into consideration the network architectural components as well as goodness-of-fit. Bayesian Regularization training technique assures network modification function which caters for improved generalization of the network during training. Bayesian regularization training technique is superior to early stopping training technique as BR training technique reduces both variance and bias during network training, while early stopping technique only reduces variance but increases bias. Figures 7 and 8 are the graphical representation training results of single-intermediate layer VNN and fixed-intermediate layer RBF-NN from Table IV i.e. training using BR training technique which gives the best training results for both single-intermediate layer VNN and fixed-intermediate layer RBF-NN models. Figures 7 and 8 are the graphs of simulation results of training single-intermediate layer VNN and fixed-intermediate layer RBF-NN with BR training technique. Bayesian Regularization is one of the training approaches being exert in NN training for network optimization and to avoid poor generalization during training as it leads to reduction of both variance and bias during network training. From Figures 7 and 8, it can be seen in Figure 7 that on application of BR training technique for training of the measured dataset, the single-intermediate layer VNN (green dots) evenly predicted all the measured dataset (blue dots) while in Figure 8, on application of the same BR training technique for the training of the measured dataset, the fixed-intermediate layer RBF-NN did not thoroughly predict all the measured dataset as can see that the green dots of the prediction using fixed intermediate layer RBF-NN did not evenly align with all the blue dots of the measured dataset. This shows that on application of BR training technique to both single-intermediate layer VNN and fixed-intermediate layer RBF-NN, training using single-intermediate layer VNN in the prediction of signal power loss with measured dataset shows superiority over training using fixed-intermediate layer RBF-NN. Also, comparison of training results of Table III and Table IV, show the results of training the measured dataset with the best performance neurons of 50 neurons in the intermediate layer of single-intermediate layer VNN and of 70 neurons in the intermediate layer of fixed-intermediate layer RBF-NN using early stopping technique and BR technique.

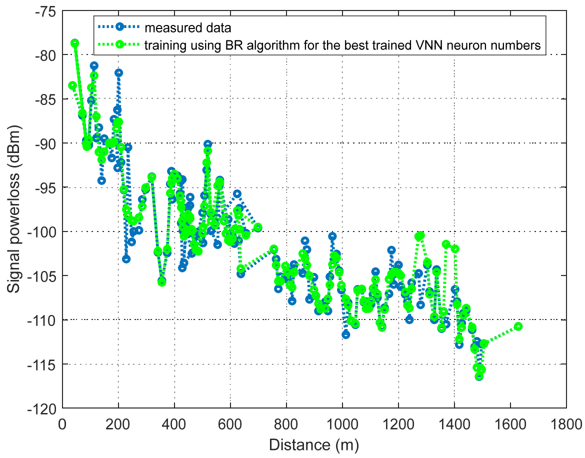

Fig. 7. Graph of re-training single-intermediate layer VNN with 50 neurons in the intermediate layer exerting BR Training technique

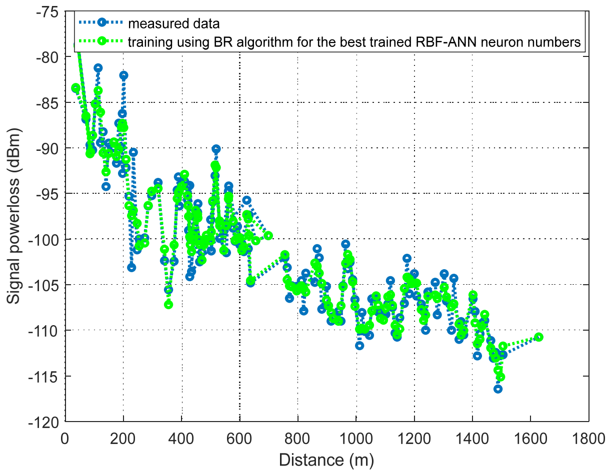

Fig. 8. Graph of re-training fixed-intermediate layer RBF-NN with 70 neurons in the intermediate layer exerting BR Training technique

The results show that BR training technique has superior training performance over training using early stopping training technique as BR reduces both variance and bias during network training thereby avoiding poor generalization of the neural network during training while early stopping training technique results to reduction of variance but not bias during network training.

VI. Conclusion

This research work studied and analyzed the performances of fixed-intermediate layer RBF-NN and single-intermediate VNN in the prediction of electromagnetic signal power loss using measured data from a LTE micro-cell built-up environment. The neurons in the single-intermediate layer VNN and the fixed-intermediate layer of RBF-NN were varied from 10 to 70 and the network training carried out using two training techniques: the BR and early stopping training techniques. The training results show improved prediction performance of single-intermediate VNN over fixed-intermediate RBF-NN as the single-intermediate VNN required lesser number of intermediate layer neurons for better network training and prediction than the fixed-intermediate layer RBF-NN. Also, BR training technique shows superiority over early stopping training technique as BR training technique demonstrates reduction in both variance and bias thereby resulting in better network generalization while the early stopping training technique only shows reduction in variance but not bias. 1st order statistical indices, the *RMSE*, the *MAE*, the *SD* and the *r* were employed for result analysis.

Among future research works will be focus on the implication of various NN hyper-parameters for enhanced prediction of signal power loss using NN models.

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