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Performance Comparison of ANN Training Algorithms for Hysteresis Determination in LTE networks

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Abstract.

Long-Term Evolution (LTE) network is an improved standard for mobile telecommunication system developed by the 3rd Generation Partnership Project (3GPP) requires an efficient handover framework which would reduce hysteresis and improve quality of service (QoS) of subscribers by maximizing scarce radio resources. This paper compares the performance of two ANN prediction algorithms (Levenberg-Marquadt and Bayesian regularization) based on received signal strength (RSS) and the hysteresis margin parameters for neuro-adaptive hysteresis margin reduction algorithm. The Bayesian regularization algorithm had a lower mean error when compared with the Levenberg-Marquadt (LM) prediction algorithm and as such a better option for neuro-adaptive hysteresis margin reduction algorithm.

1. Introduction

In Mobile communications systems, the UE regularly moves through several base stations (BS). As a UE enters the region served by a new BS, the call connection is reassigned from the BS previously serving that UE to the new BS [1]. The LTE technology is designed towards performing uninterrupted and smooth handover processes in order to utilize its network resources to the utmost. The handover process can be carried out either by the network itself or the user equipment (UE) to prevent disruption in services rendered with improved quality. The handover triggered by the UE occurs due to detection of poor signal strength received from the serving cell. Network initiated handovers are performed generally in order to reduce or avoid the probability of dropped calls which may occur due to network congestion. Regardless of user position or attachment point, an active connection is sustained for network users. Speaking in broad terms, handover between base stations are of two types; vertical/heterogeneous and horizontal/homogeneous. Vertical handover, also referred to as heterogeneous handover, involves handover between base stations which utilize different access technologies. Handover involving base stations which employ same access technologies is called horizontal handover or homogeneous handover. It is the desire of network operators that handover is initiated at the appropriate time and users be connected to the most adequate network with the aim of promoting the quality of service (QoS). Handover Initiation, decision and execution are three procedures that occur in the handover process. The first step is handover initiation, includes an



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accurate estimation to determine if handover is necessary and a generation of triggers to begin the handover process. Handover decision entails examining set criteria for selecting the most appropriate target cell and the final stage, handover execution, deals with the actual connection to the target network after carrying put several handover processes [2].

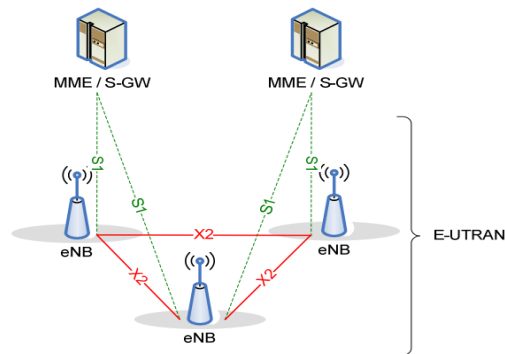


Figure 1. LTE system architecture, source [3]

In LTE networks as well as mobile communication systems in general, the user equipment (mobile station) moves across several eNodeBs (base stations) and at each point in time a considerable signal level is needed to maintain an uninterrupted call connection. Each eNodeB serves a particular region and as the user equipment (UE) moves towards an eNodeB (also known as target eNodeB), the received signal strength (RSS) of the eNodeB currently serving it deteriorates. The UE regularly measures the RSS of the serving eNodeB and that of the target eNodeB at different time intervals. This, among other parameters, allows for the UE to be reassigned to the target eNodeB from the serving eNodeB the minute the UE records poor signal strength from the serving eNodeB. This process or reassignment is called handover and figure 2 shows the steps involved in this process.

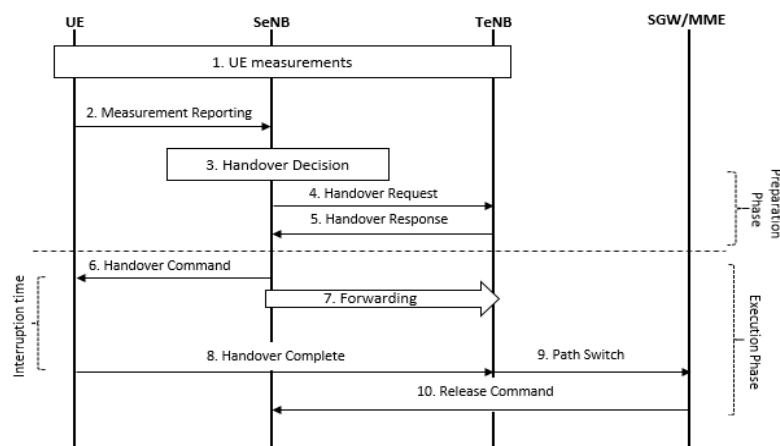


Figure 2. Steps in the handover process, source [4]

In designing handover algorithms, the quality of the link is a necessary parameter to consider and this can be analyzed using signal strength. According to [5] handover algorithms can be designed based on received signal strength (RSS), speed of UE, cost function, level of signal interference and energy efficiency. This paper adopts the RSS based handover algorithm which puts into consideration the hysteresis margin. [2] defines the hysteresis margin as a margin needed for keeping the minimum difference between the RSS of the serving eNodeB and that of the target eNodeB:

$$S_t^{Tar} > S_t^{Ser} + HM \quad (1)$$

Several improvement mechanisms (such as fuzzy logic, deep learning) have been deployed in the handover process to improve efficiency. Nowadays, handover algorithms are integrated with numerous prediction frameworks which allows for storage of previous handover data and determination of future handover decision criteria based several mathematical estimations. ANN, being one of such prediction and efficiency improvement mechanisms, is used in this research to determine the appropriate hysteresis margin to assign in a handover process based on the RSS of both target and serving eNodeB. This paper analyzes and compares the training results from two ANN training algorithms; Levenberg-Marquadt and Bayesian Regularization, used in the training 70 datasets. The best results put of the two training algorithms is adopted in the LTE network.

2. Literature review

Artificial Neural Network (ANN) employs the concepts of operation of the human brain and is an effective tool for deriving exact results for inputs non-existent in the process of training a given dataset [6]. A research on adopting the multi-layer perceptron (MLP) technique in neural networks for decreasing handover delays in LTE networks was carried out by [7, 25, 26]. Just like [8], the research utilized the same enhanced technique which adopts historical data for handover delay reduction using criteria such as packet loss, time and region domain, and time it takes an eNodeB to reply. As stated by the authors, in order to attain homogeneous communication quality, the eNodeB send a notification to the UEs informing them of the strength of signal and for the UEs to brace themselves for handover. The research proposes that the processes involved in the handover (preparation, execution and completion) tend to take time as it can lead to a breakdown and loss of data in the search for and selection of a target eNodeB. This analysis led to development of a prediction model that predicts the direction of signals and angles of the eNodeB using the MLP neural network. The proposed model is of the assumption that the UE is in motion and uses a GPS to determine the positions of the eNodeB and the UE at every point in time. Information gotten on the eNodeB is stored and that of UE is also stored in order to predict its motion direction. The angle between each UE position is also calculated giving the precise direction of motion. Based on these two criteria, direction and angle, adopted and the information stored for handover prediction, the UE can decide to connect or skip connecting to a target eNodeB. As the UE keeps moving to new regions, the previous history data is updated and the new data about each eNodeB in that region based on UE position, direction and angle is stored. The MLP with a sigmoid function integration, is employed to sieve out the undesired eNodeB by carrying out a comparison between the saved angle data and the angles of the eNodeB in neighboring cells. If the new angle data is not equal to the saved angle data, the UE is instructed to skip the eNodeB in order to decrease time spent in carrying out the handover processes. The proposed model picks the eventual target eNodeB based on direction of motion of the UE and the coverage region of the target eNodeB. MATLAB was used for simulation and simulation parameters include; number of eNodeB and UEs set to 19 and 57 respectively, 2GHz frequency, Bandwidth of 5MHz, a 19-site cell layout, mobility model set to random, and UE speeds of 3, 30, 120 and 150km/hr. A mobility pattern table is utilized to inform the UE about each eNodeB present in its position and other parameters like signal strength, angle of UE from eNodeB and the latter's capacity, packet loss and a mean load quota. Angles 0 and 120 degrees are adopted for analysis of rapid and robust signal strength. Results obtained reveal that, eNodeBs not deemed fit to be target eNodeBs, are skipped in order to attain a decrease in handover delay, data packet loss and duration spent in searching for a

suitable target eNodeB. In comparison with other handover techniques, the results proffers that under the velocities analyzed in the research, the presented model is superior in terms of general mean average signal transmission and handover delay time, and packet loss. The results confirm that through selection of an exact target, mean handover delay time is decreased by about 22% leading to a corresponding 19% reduction in data packet loss and a 3% decrease in the overall mean packet delay. As a resulting effect, [9] stated that the power engines of UEs are save making it more efficient.

The proposed system model in [10], for optimum handover performance optimization, chooses distinct handover parameters for diverse scenarios and this is as a result of the fluctuations in radio conditions. Four criteria were considered for development of the system model; channel models (channels in urban and rural regions), handover principles in LTE, handover system metrics (RSRP and SINR), two key handover parameters (handover offset and Time to Trigger) and a defined criterion called the Key Performance Indicator (KPI). The KPI was defined based on rate of handover failure, rate of occurrence of the ping pong effect and the several set optimizations goals. The proposed mathematical defined different variables and utilized different mathematical procedures and these include; multivariate nonlinear regression method, fitting function of handover failure and ping pong rate, least square estimation and modification of an already existing mathematical model. Simulation adopts a 19 site hexagonal grid with 3sectors per site and an inter-site distance of 1116m, carrier frequency set to 2GHz, 50km/her uniform UE velocity, Time to trigger (100, 160, 256, 480 and 512) and 25 UE per cell. Other simulation adoptions include carrier bandwidth, simulation time and offset. Simulation results with a corresponding matching error analysis carried out during the simulation process, reveal that developed model which integrates fitting functions have a mean match capacity exceeding 90% as regards rate of handover failure and ping pong.

This result is then compared with existing prediction models and found out to be practical enough for adoption in handover prediction. In [11], a handoff decision algorithm was proposed which is based on artificial neural network. The authors attempted to use the ANN based handoff algorithm to minimize the handoff latency in wireless heterogeneous infrastructures. Choosing appropriate parameters such as the data rate, RSSI and monetary cost as input, and using the Levenberg Marquardt training algorithm, the results obtained was compared with some other artificial intelligence algorithms. Based on the results obtained by the authors in this work, the neural network handoff decision algorithm was able to switch between different access network technologies. The authors were also able to determine that the use of ANN based algorithm can significantly minimize handoff latency while maintaining the number of handoffs [11, 28, 29]. [12] also discussed the use of neural networks for vertical handoff algorithms. In their approach, the artificial neural network is utilized to take handoff decisions based on the bandwidth and received signal strength. The mobile terminal of the proposed method periodically performs measurements of the parameters of two different networks before vertical handoff decision is taken. The utilization of ANN in vertical handoff decisions have proved very useful and efficient and the adoption of Levenberg Marquardt algorithm have made the entire training period of the neural network model faster. However, the authors in this research only considered the RSS and bandwidth in taking handoff decisions. Parameters such as the cost and network delay which can also impact performance were not considered [12, 26, 28]. In [13] a mobility-based call admission control using artificial neural network was proposed. In their work, they identified mobility management and resource utilization as the two most important issues in wireless multimedia networks. They utilized artificial neural

network to be able to accurately predict the future position of mobile users depending on the mobility history of the user in order to provide more guarantee of handoff probability. The authors in this research work utilized the back propagation neural network model. The proposed scheme was also capable of accurately predicting where and when and in which cell the next handoff will occur. This method as developed by these researchers was able to increase the ration of mobility prediction while reducing the handoff dropping probability to a very reasonable extent [13, 27, 28].

3. Model Design

This research focuses on integrating ANN in the initiation stage of LTE mobile handover. Figure 3 shows the model used. It has two parts: the preliminary phase and the ANN prediction stage.

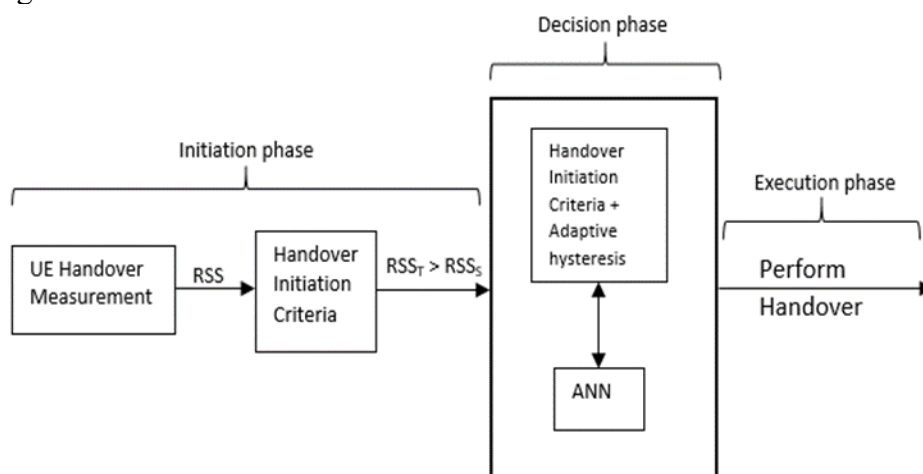


Figure 3. Framework of Research

3.1. Preliminary Phase

Figure 4 shows the flowchart of the preliminary phase. It includes the following steps:

- Check measurements
- Check if $RSS_T > RSS_S$
- If “ $RSS_T > RSS_S$ ” is satisfied, apply adaptive hysteresis margin, h ; $RSS_T > RSS_S + h$
- Input RSS_S and RSS_T into ANN

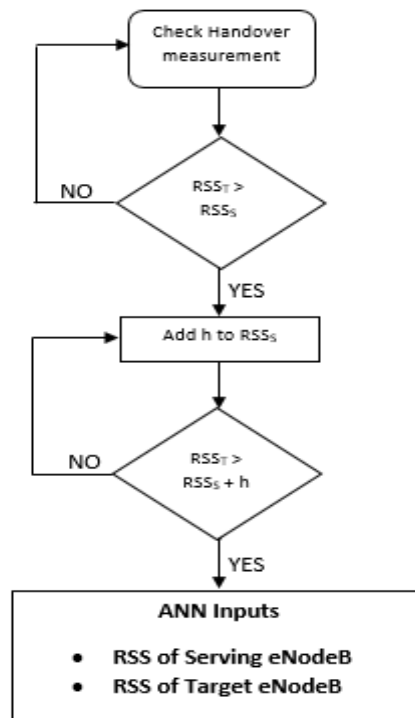


Figure 4. Preliminary stage of the Neuro-Adaptive model

3.2. ANN Framework of model

ANN comprises of several neurons organized in a systematic pattern. The summing function, activation function and synaptic weights are three primary components of the neuron. Activation functions range from hard limit, log-sig, linear and tan-sig. The ANN usually contains more than one neuron and the output of a neuron, k , is defined by the equations below [14]:

$$u_k = \sum_{j=1}^p w_{kj} x_j \quad (2)$$

$$y_k = f(u_k - \theta_k) \quad (3)$$

Parameters $x_j (j = 1, \dots, p)$ represent the inputs of the neuron, $w_{kj} (j = 1, \dots, p)$ represent the weights of the neuron while θ_k , $f(\cdot)$ and y_k represent the threshold, activation function and output of the neuron respectively. Figure 3.5 shows the procedures involved in the ANN application process.

In the Neuro-Adaptive Hysteresis Handover Algorithm (NAHHA), the Received Signal Strength of serving BS (RSS_S) and Received Signal Strength of target BS (RSS_T) are used as input parameters while the output parameter is taken to be the hysteresis margin. For a given RSS_S and RSS_T a certain value of the hysteresis is attained. The ANN data is then inputted into the LTE network and handover decisions are made based on the inputted data. Table 1 shows the input and output parameters respectively.

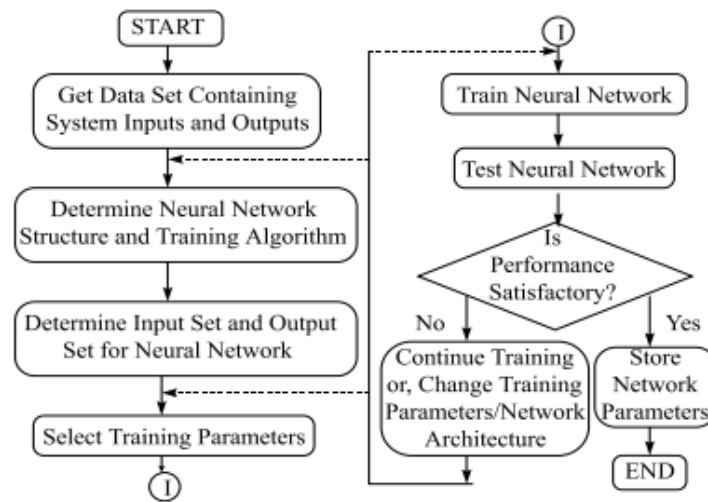


Figure 5. ANN application process, source [15]

Table 1. Input and output ANN parameter

Input parameters	RSS of serving eNodeB	RSS_S^t
	RSS of target eNodeB	RSS_T^t
Output parameter	Adaptive HM values	h^t

The mapping, as defined in [16], involving the input parameters and that of the output is illustrated by the non-linear function f^t , given by;

$$h^t = f^t(RSS_S, RSS_T) \quad (4)$$

4. ANN Training Functions

4.1. Levenberg-Marquadt Algorithm

This algorithm, also known as the damped-least squares method, identifies the least value of the multivariate function that can be conveyed as the sum of squares of non-linear real-valued functions [17]. It was designed to attain a second-order training speed without the necessity of computing the hessian matrix and work explicitly with loss functions which adopt the form of a sum of squared errors [18], [19]. The algorithm adopts an iterative mechanism in which the performance functions are always decreased for each iteration process undertaken by the algorithm. This aspect of this training algorithm makes it the fastest compared to all other training algorithms for average-sized networks.

4.2. Bayesian Regularization Algorithm

A neural network scheme utilizes a set of data with the intent of training and produces an output of the scheme based on the training and also testing models. During the training process, the scheme shows little and roughly same error for all stages of both testing and training. The regularization technique restrains the neural network to converging to a set of weights and biases having lesser values [20], [21], [22]. The Bayesian regularization training algorithm has

a high level of functionality in comparison to standard back propagation networks and can decrease or eradicate the need for tedious cross-validation processes. It is a mathematical operation in which non-linear regression is transformed into an organized statistical problem [23]. One advantage of this training algorithm besides having a high functionality level, is the validation process, adopted in normal regression methods such as back propagation, is not considered necessary. Overtraining the network using the trainer is difficult. This is as a result of its procedures providing a targeted Bayesian criterion for training to stop. Over-fitting the network is also difficult as the trainer calculates and trains several numbers of valid network parameters/weights, and eliminating those that are invalid [17].

4.3. Regression Plot

The R values in the regression plot show the correlation between the inputs (RSS_S , RSS_T) and the output (hysteresis). R tending to 1 or when R is equal to one, shows a close relationship between both parameters. An R value of 0 shows a random relationship between the parameters.

5. Training Process and Comparison

70 datasets, establishing the relationship between the inputs (RSS_S and RSS_T) and the output (hysteresis value) generated using LTE handover simulation in MATLAB, were used to train the algorithms. Each algorithm; levenberg-marquadt and Bayesian regularization, are subjected to the same system conditions. Results are then compared and the best algorithm for the NAHHA is determined. Figure 6 below shows the neural network architecture used for both algorithms.

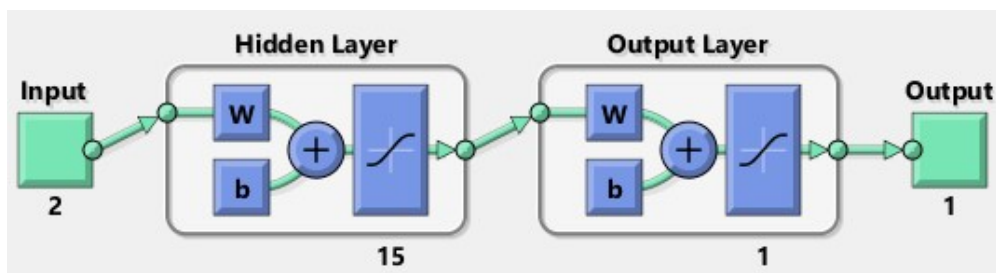


Figure 6. Neural Network Architecture

5.1 Bayesian Regularization

Figures 7 and 8 show the training of the datasets using the Bayesian regularization algorithm and the resulting regression plots

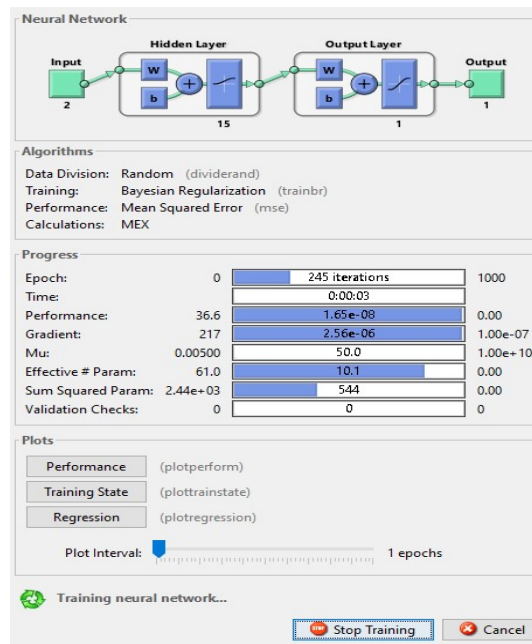


Figure 7. Training process of datasets using Bayesian Regularization

The regression plot in figure 7 shows a good correlation between the inputs (RSS_S and RSS_T) and the target (hysteresis) using the Bayesian regularization training algorithm. The R values give 1 for both training and testing.

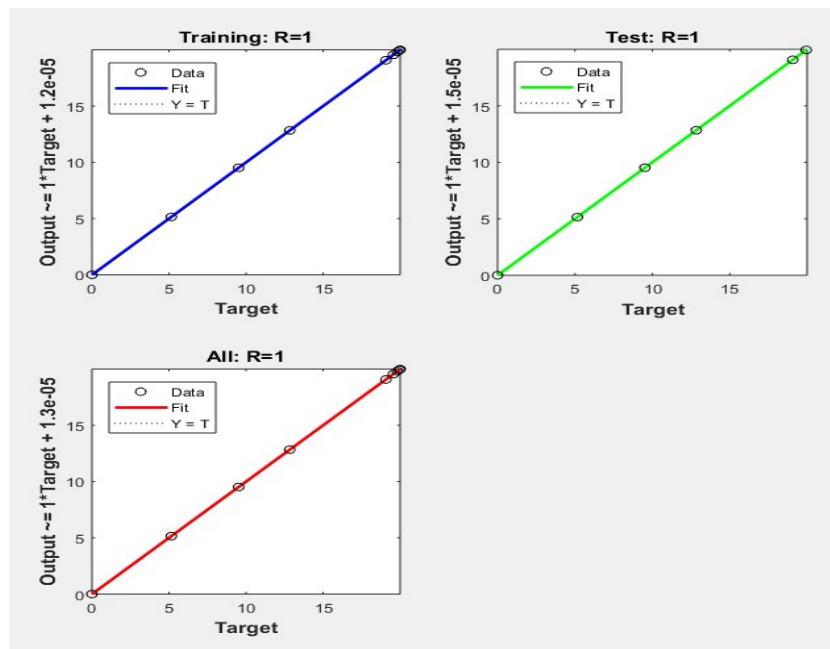


Figure 8. Regression plot for Bayesian Regularization

5.2. Levenberg-Marquadt Algorithm

Figures 9 and 10 shows the training of the datasets using the Levenberg-Marquadt algorithm and the resulting regression plots.

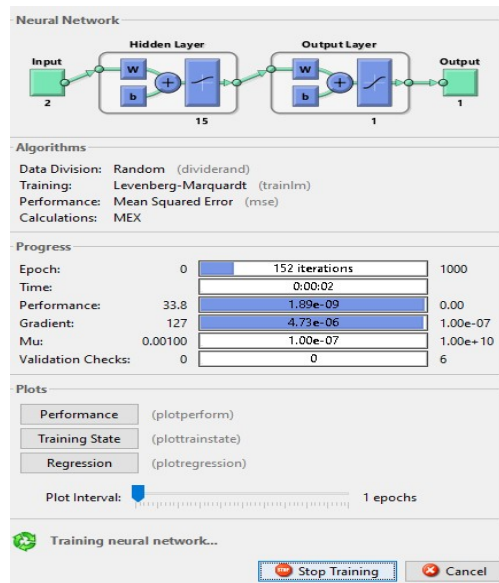


Figure 9. Training process using Levenberg-Marquadt

The R values for the Levenberg regression plot gives a 1 for training, validation and test. These R values signify a close relationship between the input and target values.

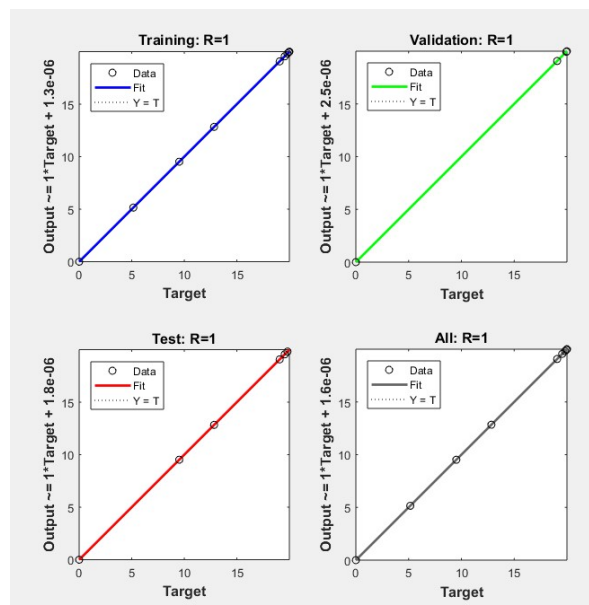


Figure 10. Regression Plots for Levenberg-Marquadt

6. Results and Discussion

After the training algorithms using the 60 of the 70 datasets, 10 datasets were used to test the prediction accuracy of each of the algorithms. This is done in order to pick the best training algorithm to adopt in the Neuro-Adaptive Hysteresis Handover Algorithm. An overall

percentage increase was calculated for both Bayesian regularization and Levenberg-Marquardt using the formula:

$$\frac{\text{Predicted HM value} - \text{Actual HM value}}{\text{Actual HM value}} \times 100 \quad (5)$$

Table 2 show the comparison between predicted values using each algorithm and the actual values gotten from the LTE simulation using MATLAB:

Table 2. Comparison between actual and predicted values for both training algorithms

RSS_T (dBm)	RSS_S (dBm)	Actual HM(dB)	LM Predicted HM (dB)	BR Predicted HM (dB)	% Error(LM)	% Error(BR)
-114.832	-116.45	6.7606	6.8903	6.8541	1.9185	1.3830
-113.128	-122.764	11.066	11.1448	11.1448	0.7121	0.7121
-111.627	-127.552	14.2857	14.35	14.3461	0.4501	0.4228
-110.886	-129.22	15.302	15.3338	15.3244	0.2078	0.1464
-109.974	-130.86	16.2896	16.1923	16.2572	-0.5973	-0.1989
-109.106	-132.3	17.067	17.0936	17.0939	0.1559	0.1576
-108.778	-133.621	17.8278	17.8869	17.8884	0.3315	0.3399
-107.089	-134.722	18.281	18.28	18.2936	-0.0055	0.0689
-105.893	-135.365	18.5429	18.6006	18.5983	0.3112	0.2988
-103.724	-137.187	19.2533	19.2882	19.2941	0.1813	0.2119
Total Error (%) (Mean Error (%))					3.67 (0.367)	3.54 (0.354)

The predicted values using the Bayesian Regularization algorithm gives a 3.54% total percentage increase in the hysteresis margin (HM) when compared to the actual hysteresis values. That of the Levenberg-Marquardt algorithm incurs a 3.67% overall increase when compared to actual HM values. A lesser percentage increase connotes closeness to the actual values. A 3.54% overall HM increase recorded using the Bayesian Regularization made this algorithm the more appropriate choice. This algorithm is also suitable for noisy and minute training datasets and this also makes it the better choice as only 70 datasets were used for training.

7. Conclusion

This research adopted the Artificial Neural Network (ANN) improvement tool in LTE network for determining the appropriate hysteresis margin for a handover process, based on the Received

signal strength (RSS) of both target and serving eNodeB measured by the UE. MATLAB was used for simulation and the acquired data was trained using two ANN algorithms; Levenberg-Marquadt (LM) and Bayesian Regularization (BR). The training results were compared in order to know the algorithm most suitable of the two for neuro-adaptive handover hysteresis margin reduction for LTE network. The Bayesian Algorithm gave better training results when compared to that of the LM and is recommended.

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