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Performance Evaluation of Neural Network based Cognitive eNodeB in LTE Uplink

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ABSTRACT: In this paper, a feed forward random neural network (RNN) with gradient descent (GD) and Levenberg Marquardt (LM) training algorithm based framework is used to improve inter cell interference coordination (ICIC) and radio resource management (RRM) in LTE system. A neural network based cognitive engine is embedded within eNodeB which co-ordinately suggest optimal radio parameters to the users, and best transmit power to the operating users by neighbouring cells. Long term learning, fast decision making , and less computational complexity are the three main requirements to map CE to distribute systematically in any cognitive communication system and most of the present techniques used as a cognitive solution lack in. The mechanism of feed forward network supported framework is examined with traditional schemes. To ensure a better performance of the system, the results are verified and compared with traditional schemes.

KEYWORDS: Energy Efficiency; Machine Learning; Random Neural Network; LTE uplink

I. INTRODUCTION

An unrivalled increase in the demand of mobile data access has been observed in the recent years. To deploy solution, 3rd Generation Partnership Project (3GPP) defined LTE system. Transmit power is one of the most important parameter in LTE uplink, which can communicate the problems comprises from channel fading, ICI, user equipment (UE) immoderate transmission power, and adjacent –channel interference (ACI). 3GPP deploy different solutions and techniques such as FPC for LTE uplink as an open loop power control (OLPC), which works on the assumption that interference generated towards other cells is generally because of cell-edge users However, corresponding interference ensue a different trend which affirm the assumptions that users experiencing the lowest path gain generate most of the interference is not always true [1]. This concludes that variations in the power will lead us to equilibrate the effect of generated interference, not by the path gain.

In the previous work, many publications have marked the functioning of ICIC and RRM schemes and they have presented the solutions with variation in approaches from statistical, analytical, and classical network optimization schemes to self-organized approaches [2][3]. To pursue modern services of the radio system such as autonomous computing and optimization, the implemented radio system must have partial or complete idea about the working electromagnetic environment, user equipments, and the unwanted parameters which may affect the system beforehand. The definition of cognitive radio fulfils the system requirements and which can be better solution for the improvement of ICIC and RRM. To make such design possible, many authors have been published a work on AI/ML techniques.

In [4] the authors work on the interference management schemes for multi cell of isolated cell LTE system and mitigate the scarceness of the traditional schemes with the help of cognitive base stations (CBSs). They conclude with the decrease in co-channel interference and also observe that the CBSs can use their knowledge of radio environment to adaptively allocate resources. To make traditional cognitive real time radio systems as an intelligent system with the help of AI/ML techniques the system must have better learning ability and it must act intelligently. This can be done by training the CE with desired parameters in corresponding environment. During the training of CE, the training speed, accurate learning, computational complexity, and available training samples are of dominant importance to the system operational performance and also limiting factors for CR to reach best configuration settings in real-time application. An earlier lot of research has done to solve CE training problems and they made a conclusion that the CE can be trained in a moderate amount of time and effort.

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A problem with traditional AI/ML techniques is retraining, which occurs in the situation in the process of exploitation while training CE, the radio may not be aware of the acceptable solutions to the actual problem, and this can consume additional time and energy. To avoid the process of retraining, the one must have to consider different operating environments while training CE, and for real time implementation it is difficult. If radio is operating in critical mission, there may not be enough time to retrain CE again and again. Accordingly, to severe change in environment, the long term learning is capable to avoid retraining.

Inadequacy of long term learning with fast decision making and less complexity having limiting factors of ANN and many other AI/ML conceptualizations. In [5] authors proposed Q-learning based collective interference control scheme and shown a structure which combined ANN and reinforcement learning (RL). Whereas, ANN go through limited generalization, slow calculation rate at run-time, local minima, and over-fitting problems. Stochastic-learning and proactive resource allocation based gradient algorithm for adaptive power control with the help of support vector regression is presented in [6]. In [7] a game theory based joint power and interference control framework for LTE-downlink is demonstrated. However, the system is having some limitations like it requires user specific utility parameters, which cannot be possibly taken in many situations [2].

It is found that the lack of study has been seen to achieve CE design features. The intrinsic properties of RNN, makes RNN a better choice for CE design [8]. In the previous work [9], authors presented the advantage of RNN over ANN with respect to their learning ability, complexity, and the generalization. In [10] the convergence speed and local minima problems of gradient descent (GD) based RNN by implementing genetic algorithm (GA), differential evolution (DE), and adaptive inertia weight particle swarm optimization (AIW-PSO) training algorithms. The real time comparison with different LTE environment has been demonstrated in the paper [11].

Therefore, our main efforts in this paper are: (1) Earlier RNN is used to improve the effect of ICIC and RRM in LTE uplink. In our work a new floor which helps to reduce the effect of ICI with zero bandwidth loss and collectively undertake both power and MCS selection has been introduced.

Earlier authors worked separately for the same contents. The changes in the system targets to program optimal transmit power and MCS to the attached user equipments (UEs) and also help to suggest satisfactory transmit power to the UEs served by neighbouring cells. The base station (BS) has power to control user specific power, thus to instruct mobile station (MS) to transmit power essential for uplink transmission , the channel quality information has to be sent by MS to the BS which is done by calculating optimal uplink transmit power level. (2) The proposed CE is evaluated with respect to the necessary requirements of CE design. In real time cases there can be training/retraining time restrictions, in that cases the proposed CR can check practicability and solidity. The training of CE is done with ANN and RNN datasets, where we contend ANN as a reference for RNN. (3) Levenberg marquardt (LM) and GD are used to minimize the cost function, while in previous work the there only focus is to consider GD (4) The comparison of the performance improvement in terms of training time and minimum square error of our proposed RNN with ANN is done.

The organization of paper followed by Section 2, which introduces the field of study including system model, assumptions and calculations, scheduling, and CE design. In Section 3 a brief introduction of RNN has been given. Section 4 shows experimental results and discussion. Section 5 concludes the work and discussed future work.

II. FIELD OF STUDY

In [2] authors used average residual battery level of the entire network and it was calculated by adding two fields to the RREQ packet header of a on-demand routing algorithm i) average residual battery energy of the nodes on the path ii) number of hops that the RREQ packet has passed through. According to their equation retransmission time is proportional to residual battery energy. Those nodes having more battery energy than the average energy will be selected because its retransmission time will be less. Small hop count is selected at the stage when most of the nodes have same retransmission time. Individual battery power of a node is considered as a metric to prolong the network lifetime in [3]. Authors used an optimization function which considers nature of the packet, size of the packet and distance between the nodes, number of hops and transmission time are also considered for optimization. In [4] initial population for Genetic Algorithm has been computed from the multicast group which has a set of paths from source to destination and the calculated lifetime of each path. Lifetime of the path is used as a fitness function. Fitness function will select the highest chromosomes which is having highest lifetime. Cross over and mutation operators are used to enhance the selection. In [5] authors improved AODV protocol by implementing a balanced energy consumption idea

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into route discovery process. RREQ message will be forwarded when the nodes have sufficient amount of energy to transmit the message otherwise message will be dropped. This condition will be checked with threshold value which is dynamically changing. It allows a node with over used battery to refuse to route the traffic in order to prolong the network life. In [6] Authors had modified the route table of AODV adding power factor field. Only active nodes can take part in rout selection and remaining nodes can be idle. The lifetime of a node is calculated and transmitted along with Hello packets. In [7] authors considered the individual battery power of the node and number of hops, as the large number of hops will help in reducing the range of the transmission power. Route discovery has been done in the same way as being done in on-demand routing algorithms. After packet has been reached to the destination, destination will wait for time δt and collects all the packets. After time δt it calls the optimization function to select the path and send RREP. Optimization function uses the individual node's battery energy; if node is having low energy level then optimization function will not use that node.

A. Framework

In LTE uplink, ICI which is considered as contact between resource blocks (RBs) [11], and to reduce the same power control strategy can be used. To verify the performance of the system, the basic LTE system has been used with 7 cell hexagonal layout having omnidirectional antennas at the centre of the corresponding cells, as shown in Fig. 1[11]. A RNN-CE has to deployed in the corresponding reference cognitive-eNodeB. MCS and power p_0 are the configuration parameters of reference cell UEs and for adjacent eNodeB UEs, power ($p_1, p_2, p_3, p_4, p_5, p_6$). Once C-enodeB is attached, it is responsible for monitoring, configuring UE, and also to manage radio resources. This is the phenomenon which has to be done for the implementation of the proposed system.

B. Assumptions and calculations

As per 3GPPs LTE technical specification, the best we have taken to analyse the performance of LTE system. For the implemented system, the carrier frequency of the synchronic systems were set to 2000MHz for urban, suburban, and 900MHz for rural with inter-site distance of 750m. OFDMA urban macro propagation model is used. Antenna gains for BS and UEs were assumed to be 15dBi and 0dBi. 8 UEs per cell i.e. 24 RBs per BS and 3 per user were assumed. In addition, bandwidth of RB: 180 kHz; thermal noise density: -174dBm/Hz; system bandwidth: 10MHz; log-normal shadowing variance: 10dB with correlation; minimum coupling loss (MCL): 70dB; handover (HO) margin: 3 dB; BS noise figure: 5dB; UE min and max transmit power: -30dB dBm to 24 dBm were the system settings. The FPC settings, OFDMA LTE link to system level mapping, adjacent channel leakage ratio/unwanted spectrum mask were the same as given in Qualcomm STG(08) 13 and 3GPP technical specification [12].

Firstly, at the discrete speed value i.e. 0/3/30/100 kms./hr. Random positions of UEs were selected. Depending on the HO margin, path loss, antenna gain, and log normal fading, the UEs get attached to the most befitting BS. The quality of service (QOS) is having requirements; the connected UEs were scheduled for every iteration and allocate certain amount of resources. For the utility of MS, every BS goes through all MSs on its served mobile list and try to add their requested sub-carriers until all MSs are served.

The signal to noise interference noise ratio (SINR) and throughput for each UE with respect to link to system level mapping is determine as follows:

$$S(m,n) = p_t(m,n) * pathloss_{effective}(UE_{m,n}, BS_m) \qquad \text{eq. (1)}$$

Where $S(m,n)$ is the received power at m^{th} serving C-eNodeB from the n^{th} UE, p_t is the transmit power of UE in dBm, and $pathloss_{effective}$ is the effective path-loss which considered MCL as defined in [11]. The bit rate for all uplink users is collected as follows:

$$Bit - rate = \frac{N_{SC_{per}-UE}}{N_{total-sc}} (x_{\frac{bps}{Hz}})_{SINR} \times BW_{MHz} \qquad \text{eq. (2)}$$

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Where $N_{SC_{per}-UE}$ and $N_{total-sc}$ are the number of allocated sub-carriers to each UE and total number of sub-carriers available at each BS. The $x_{\frac{bps}{Hz}}$ is the spectral efficiency with respect to calculated SNIR and BW_{MHz} is the bandwidth.

The combined ICI and ACI at reference cell is calculated as follows:

$$I(m,n) = I_{inter}(m,n) + I_{ext}(m,n) + N_t(thermal-noise) \quad \text{eq. (3)}$$

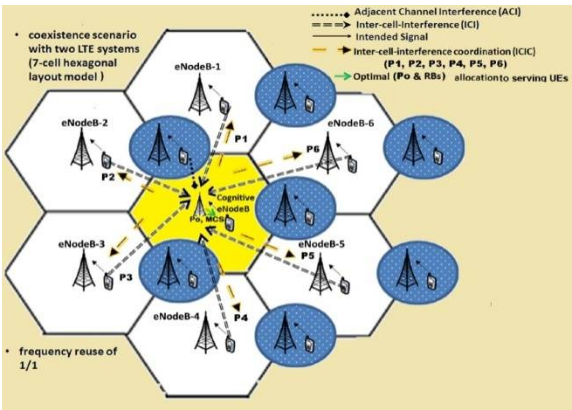

Fig. 1. System Model

Where $I_{inter}(m,n)$ is the ICI coming from the UEs of adjacent cells operating on same frequency sub-carriers and is calculated as follows:

$$I_{inter} = \sum_{l\equiv 1, l\neq m}^{N_{cell}} p_t(l,n) * pathloss_{effeective}(UE_{l,n}, BS_m) \quad \text{eq. (4)}$$

$I_{ext}(m,n)$ is the ACI coming from the UEs on adjacent channels in coexistent LTE system. ACI is the combination of $I_{unwanted}$ (unwanted emission in adjacent band) and $I_{blocking}$ (blocking effect of receiver) and is calculated as:

$$I_{ext} = \sum \sum iRSS_{blocking}(UE_{j,v}, BS_m) * iRSS_{unwanted}(UE_{j,v}, BS_m) \quad \text{eq. (5)}$$

C. Framework Planning

The aim is to achieve predicted SINR for the same, first C-eNodeB scheduler obtains particular UE, and alots RBs for uplink transmission, based on CQI and interference on scheduled RBs to accompanying transmission time interval, the embedded CE selects the optimal radio parameters (MCS and powers). Also the optimal transmit powers of UEs served by adjacent eNodeB will be suggested by CE. This process is depicted in Fig. 1 for 7 cell hexagonal layout.

D. CE Design

The optimization structure is summarized in [11], where the necessary data is collected for learning to make optimized decisions by GA based reasoning process. The respective learning module learn the changes in the channel C and calculate the performance X given radio configuration M. The vector C, M, and X are the training parameters taken from the radio. To select useful parameters for optimization section, this radio contacts with the initialized optimizer

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for current CQI and aims, then the optimizer respond back to the learning module with considered C and M. The learning section provides the close performance of considered C and M i.e. $P(X\,|\,C,M)$.

To train CE, information which is available to cognitive controller can be categories as: environmental measurements (unwanted factors effecting the reliability of communication), configuration parameters (tuning parameters), and performance metric. To check the effect of configuration parameters and environmental parameters on the performance of the system, we train RNN with the same. All this parameters are justified in (1-5).

- **Environmental measurements (C):** In this SINR, ICI, and ACI have been considered as environmental measurements.
- **Configuration parameters (C):** Here the parameters such as available channels (RBs), transmit power p_0, and MCS of all UEs served by C-eNodeB and the transmit powers ($p_1, p_2, p_3, p_4, p_5, p_6$) of all UEs served by adjacent 6-eNodeBs.
- **Performance metric:** Expected throughput for each C-eNodeB UE as a performance measure is considered.

The configuration parameters and environmental parameters are defined for input of the FFNN and the performance metric at the output of the FFNN. The input parameters are available at the respective cognitive eNodeB. Only one way communication/coordination between cognitive eNodeB to adjacent eNodeBs is required for scheduling process. With a feature set C, label set M, and n training samples $T = ((x_1, y_1),., (x_n, y_n)) \in (XxY)^n$ a ML algorithm creates a mapping $A: X \rightarrow Y$ from features to labels for new samples.

III. Random Neural Network

A RNN is mathematical representation of interconnected network of neurons or cells inspired by the spiking behaviour of biological neuronal networks. The inherent properties of RNN make it suitable for machine learning in CE. The main objective of the RNN is to transform the inputs into meaningful outputs, learn the input-output relationship, and offer viable solutions to unseen problems. RNN were first invented by Prof. Erol Galenbe [15] as a new modified class of ANNs. It offers more advantages and extemporize the limitations of ANN. In RNN, the neuron exchanges the signal in the form of spikes. The potential (k) of each neuron represents its state that increases/decreases with respect to an incoming signal. A neuron u can receive positive/negative exogenous signals, modeled as Poisson arrival streams of rates $\wedge_u$ and λ_u respectively. If a neuron receives an excitatory signal $(+1)$, its potential increases and correspondingly decreases upon receiving inhibitory signal (-1). When the potential of neuron is equal to zero ($k_i = 0$), it is in idle state and when ($k_i > 0$), the neuron is excited. In the state of excitation, the neuron fires an excitatory spike that goes from neuron u to v. In that case, the potential of neuron u decreases by one, whereas potential of neuron v increases by one. When neuron fires inhibitory spike, the potential of both neuron decreases by one. The firing is according to the Poisson process represented by the synaptic weights $w^+_{i,j} = rP^+_{i,j}$ and $w^-_{i,j} = rP^-_{i,j}$, where $P^+_{i,j}$ and $P^-_{i,j}$ are the probabilities of excitatory and inhibitory signals and r is the spikes firing rate. The $w^+_{i,j}$ and $w^-_{i,j}$ can be seen as the positive and negative rates of signal transmissions and these are the typical interconnection weights of a neural network that RNN learns through the process of learning or training. A general model of RNN is shown in Fig. 6. The average arrival rate of $+ive$ and $-ive$ signals to neuron $i(\lambda_i^+)$ and $i(\lambda_i^-)$, and the probability that neuron i is excited (q_i), are calculated using following equations:

$$\lambda_i^+ = \Lambda_i + \sum_{j=1}^{n} q_j w_{ij}^+ \quad \text{eq. (6)}$$

$$\lambda_i^- = \lambda_i + \sum_{j=1}^{n} q_j w_{ij}^- \quad \text{eq. (7)}$$

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$$q_i = \frac{\lambda_i^+}{r_i + \lambda_i^-} \quad \text{eq. (8)}$$

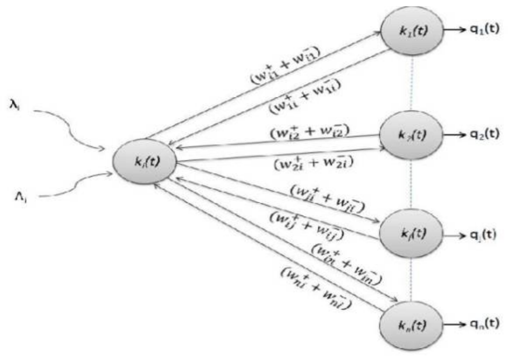

Fig. 2. A feed forward random neural network framework

A. Network Behavior in Steady State

If $0 \le q_i \le 1$ for $i = 1,2,3\ldots,n$ then stationary joint probability of network $p(k,t) = p_r = [k(t) = k]$ can be written as:

$$p(k) = \prod_{i=1}^{n} (1 - q_i) q_i^k \quad \text{eq. (9)}$$

B. Network Stability

The network is stable, if the signal potential increases with bounds. Stability can be guaranteed if a unique solution to non-linear equations (6-8) exists. The existence of solution implies its uniqueness because for any neuron i, it is not possible to have two different q_s. Moreover, in feed forward RNN, the solution always exists, since q for every neuron is computed from the values of neurons on the preceding layer [12].

C. RNN Training

The main purpose of training is to learn desired system behavior and adjust the network parameters (interconnections weights) to map (learn) the input output relationship and minimize the mean square error (MSE). The standard GD training algorithm, AIW-PSO, DE, and GA based leaning algorithms [10] was proposed earlier. However, in general there is trade off among learning accuracy, convergence time, calculation time, and computational complexity.

IV. Simulation Results

A. Simulation Assumption

The simulation studies have been conducted under MATLAB environment. We create basic LTE system model with the same initializations made by 3GPP (2009) [12]. We extract the required parameters from the modeled scenario for training a system model of neural network. We generate a data file consists the required configuration parameters, environmental measurements, and performance metric statistics for specified number of instances. Also MATLAB was used for training and validation of neural networks. RNN settings are the best we consider to get better result. The network was trained/validated with the dataset of 5000 samples. A subset of the data was used to train the neural network (NN) and rest of the data was used to compare the prediction performance of trained NN.

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B. CEs Training

The process of learning and the process of reasoning were the main computations to train CE. The decision making process is dependent on the process of learning; therefore the quality of decision making is completely dependent on the learning quality. To evaluate how well CE has learnt the system behaviour, MSE is used while training the CE; it also evaluates the performance of the learning process. Once, the system behaviour is learnt, the CE characterizes the achievable performance of possible actions i.e., the configuration parameters with respect to current situation, and then selects the most appropriate configuration parameters. The main aim of CE is achieve the least possible MSE in less training time.

C. Performance Gain

In training, different number of neurons, hidden layers and epochs were examined. The best performed RNN/ANN structures were 1 hidden layer with 11 neurons and 1 hidden layer with 20 neurons. Accordingly, In Fig. 3 we have shown the performance of the LTE system with respect to allotted UE and spotted eNodeBs. Fig. 4 shows the target achieved with greater accuracy accordingly with less time period with the help of a targeted mean square error at resulting epochs. Fig. 5, 6 shows the respective power variations in each eNodeB after training neural network.

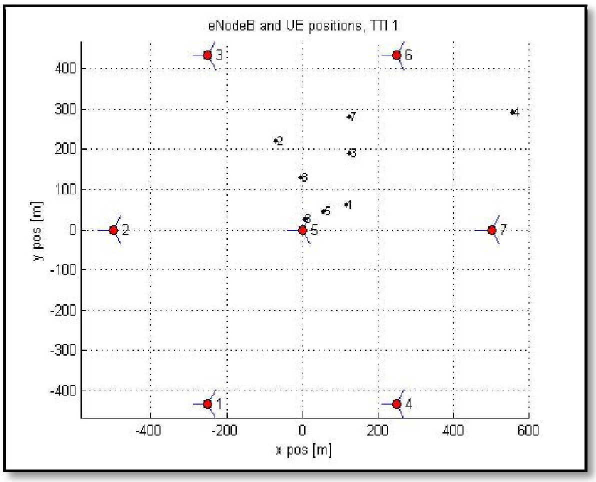

Fig. 3. eNodeB and UE positions of LTE system

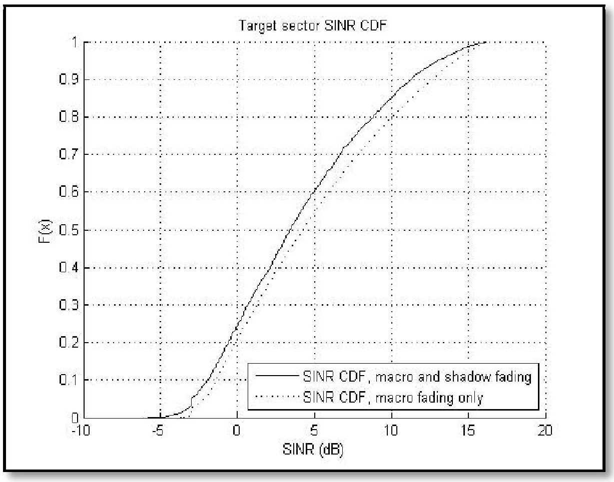

Fig. 4. Target sector SINR CDF of LTE system

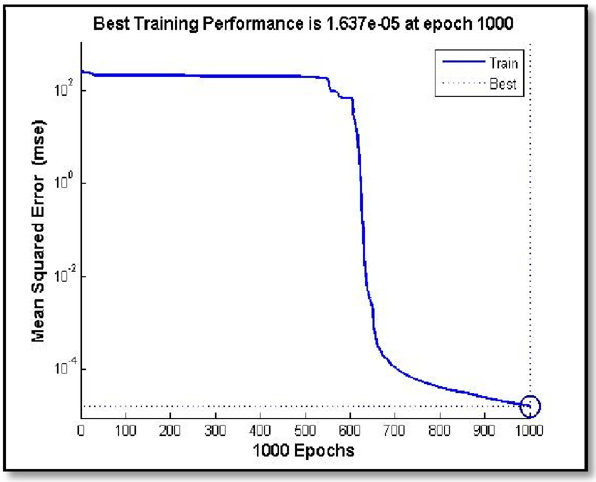

Fig.5. RNN Training Performance

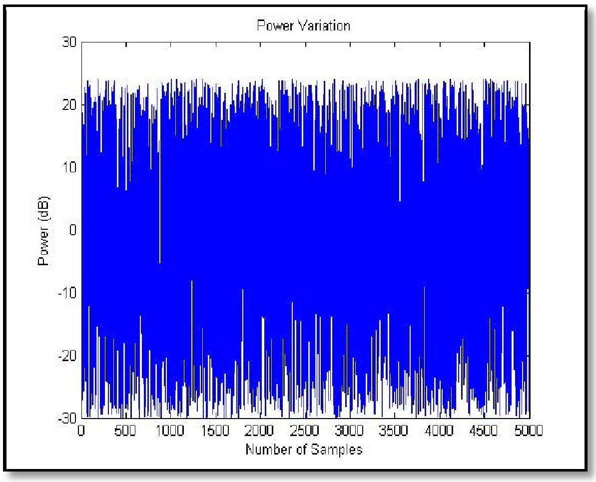

Fig.6. Power variations for 5000 samples.

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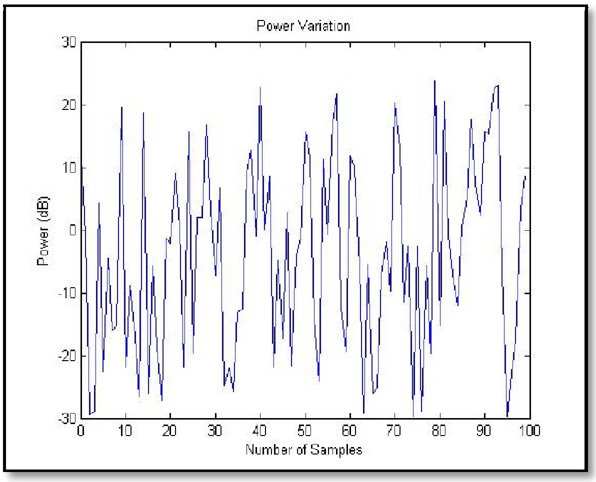

Fig. 7. Power variations for 100 samples.

V. CONCLUSION AND FUTURE WORK

The performance of feed forward RNN over ANN has been evaluated in this paper, with reference to accuracy, and training time period, and under the same LTE environmental and configuration parameters. The feed forward RNN is used as a training algorithm for CE of eNodeB and the results shows that if feed forward RNN is used over ANN while training the CE, the learning time of the CE is reduced in such manner that the performance of the system will get increased as compared to traditional training algorithm. The best performance of the system is making a conclusion that the increasing number of neurons with 1 hidden layer having less time to reach the targeted mean square error. There are further advanced RNN techniques which we have not considered for the system. We believe the use of RNN for the real time application of CR problems will create better solutions.

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