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An Intelligent eNodeB for LTE Uplink based on Neural Network

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***Abstract*— In this paper, a feed forward neural network (FFNN) 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 coordinately suggest optimal radio parameters to the users, and best transmit power to the operating users by neighboring 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—Feed Forward Neural Network (FFNN); Inter Cell Interference Coordination (ICIC); Radio Resource Management (RRM); Long Term Evolution (LTE); Cognitive Engine (CE)

I. INTRODUCTION

An unrivaled 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 pathgain generate most of the interference is not always true [1]. This conludes that variations in the power will lead us to equilibrize the effect of genrated 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 concludes with the decrease in co-channel interference and also observes 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.

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 neighboring 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 FFNN and RNN datasets, where we contend RNN as a reference for FFNN. (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 throughput and ICI of our proposed RNN and FFNN is done with state of the art FPC.

The organization of paper followed by Section II, which introduces the field of study including system model, assumptions and calculations, scheduling, and CE design. In Section III a brief introduction of FFNN has been given. Section IV shows experimental results and discussion. Section V concludes the work and discussed future work.

II. Field of Study

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 center of the corresponding cells, as shown in Fig. 1[11]. A FFNN-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 of framework

As per 3GPPs LTE technical specification, the best we have taken to analyze the performance of LTE system. For the implemented system, the carrier frequency of the synchronal 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 interference noise ratio (SINR) and throughput for each UE with respect to link to system level mapping is determine as follows:

$$S(m,n) = p_t(m,n) * pathloss_{effective}(UE_{m,n}, BS_m) \quad (1)$$

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:

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

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.

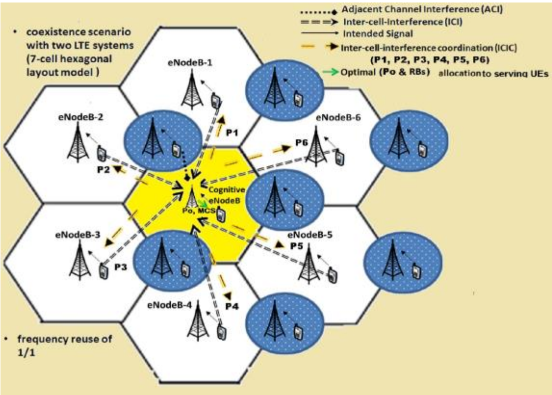

Fig. 1. System Model

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

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

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:

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

$I_{ext}(m,n)$ 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:

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

C. Framework planing

The aim is to achieve predicted SINR for the same, first C-eNodeB scheduler obtains perticular 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 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. $P(X \mid C, M)$.

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. Feed forward neural netwok

An idea behind an implementation of feed forward neural network (FFNN) algorithm is from the biological changes in the human brain. FFNN is having different number of simple neuron – such as developing units, fall in layers. Frequently these units in neural network can also be called as nodes. Every unit in the layer is reticulated with the units in previous layer. The assumptions like all the connections are equal, cannot be always true, they may have different strength or weight. The strengths on these connections can encrypt the knowledge of a network.

The basic process for using FFNN is, first we have to provide the input data to the system, and this data will get transferred layer by layer until we get it in the output side. In ideal operation it acts as a classifier, and there is no feedback present between layers. This is the reason to call them feed forward networks.

In the following figure a single neuron model is initialized.

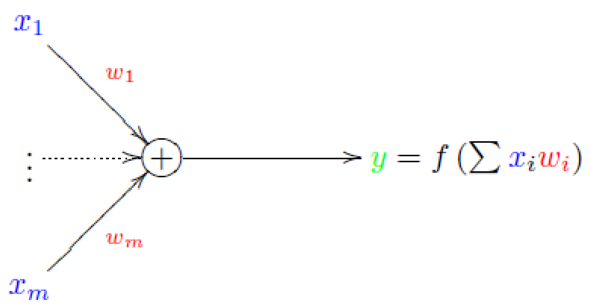

Fig. 2. A Model of a Single Neuron (Unit)

Where there are m input values by $x_1, x_2, ...x_m$. Each of the m inputs has a weight $w_1, w_2, ..., w_m$.

The input values are multiplied by their weights and summed

$$v = w_1x_1 + w_2x_2 + ... + w_mx_m = \sum_{i=1}^{m} w_i x_i \qquad (6)$$

The output is some function $y = f(v)$ of the $weighted\ sum$.

Linear function:

$$f(v) = a + v = a + \sum w_i x_i \qquad (7)$$

Where parameter a is called bias.

Heviside step function:

$$f(v) = \begin{cases} 1 & if v \geq a \\ 0 & otherwise \end{cases} \qquad (8)$$

Here a is called the threshold

Sigmoid function:

$$f(v) = \frac{1}{1+e^{-v}} \qquad (9)$$

Fig. 3 shows a schematic representation of a feedforward network. Nodes represent the neurons, and arrows represent the links between them. Each node has its number, and a link connecting two nodes will have a pair of numbers. Networks without feedback loops are called a feed-forward networks. Input nodes of the network (nodes 1, 2 and 3) are associated with the input variables ($x_1,.....,x_m$). They do not compute anything, but simply pass the values to the processing nodes. Output nodes (4 and 5) are associated with the output variables ($y_1,...,y_n$). A neural network may have hidden nodes –they are not connected directly to the environment. Neural network can have several hidden layers.

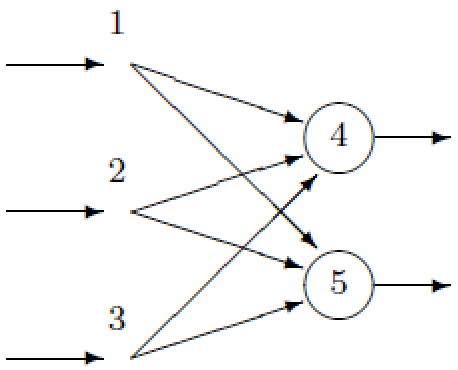

Fig. 3. A feed forward neural network framework

A. NN Traininig

The aim of training is to learn the changes in the system and accordingly adjust the parameters to predict the input output relationship and reduce corresponding mean square error (MSE). Earlier authors proposed standard GD[14], AIW-PSO, DE, and GA based learning and training algorithms [10]. However, commonly there is an interchange among computational complexity, learning accuracy, calculation time, and convergence time.

IV. Performance assessment

A. Simulation Assumptions

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. FFNN settings are the best we consider to get better result. The network was trained/validated with the dataset of 4000 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.

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. 4, 5, we have shown the performance of the LTE system with respect to allotted UE and spotted eNodeBs. Fig. 6 and Fig. 7 are showing the target achieved with greater accuracy accordingly with less time period with the help of a targeted mean square error at resulting epochs. Fig. 7 shows the respective power variations in each eNodeB after training neural network.

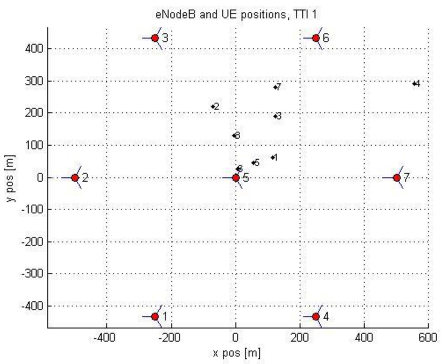

Fig. 4. eNodeB and UE positions of LTE system.

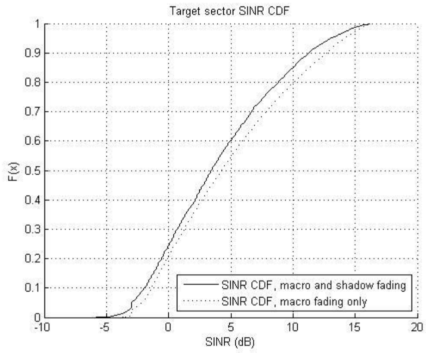

Fig. 5. Target sector SINR CDF of LTE system

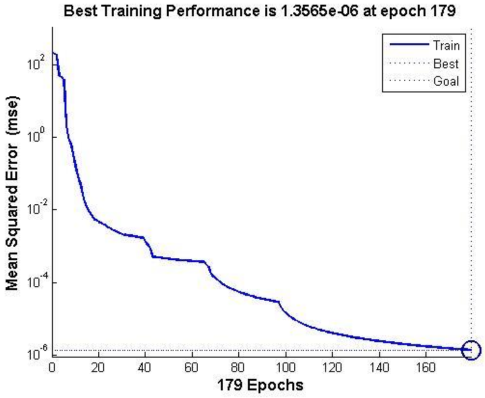

Fig. 6. Training result (20 Neurons 1 Hidden layer

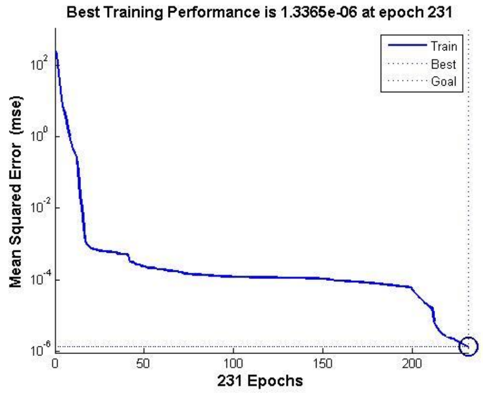

Fig. 7. Training result (11 Neurons 1 Hidden layer)

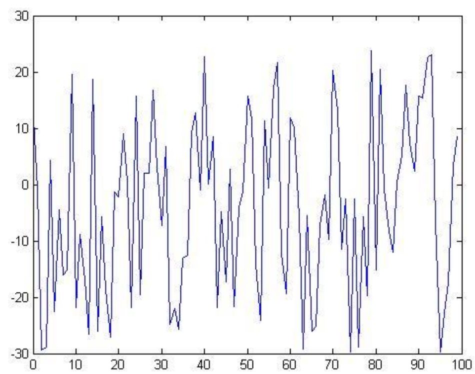

Fig. 8. Power variations in the corresponding eNodeBs

V. Conclusion

The performance of FFNN over RNN has been evaluated in this paper, with reference to accuracy, and training time period, and under the same LTE environmental and configuration parameters. The FFNN is used as a training algorithm for CE of eNodeB and the results shows that if FFNN is used over RNN while training the CE, the learning time of the CE is reduced in a 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 FFNN for the real time application of CR problems will create better solutions.

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