Intelligent Radio Resource Scheduling for LTE-Advanced using Wavelet Neural Network

Hashim Ali, Santosh Pawar, Manish Sharma

Abstract*: *This paper presents a novel technique for the efficient resource scheduling for Long Term Evaluation Advanced downlink transmission using wavelet neural network. The dynamism and the uncertainty in the resource scheduling due to the large scale of the network has been taken care through wavelet neural network. The proposed neural network based approach is trained to provide the best scheduling rule at every transmission time interval. Due to the superior estimation capability and better dynamic characteristics than conventional neural network, wavelet neural network offers a better radio resource scheduling. The objective of the proposed scheme is to enhance the system throughput, spectral efficiency and the system capacity. The simulation analysis is performed to verify the effectiveness of the theoretical development..

Keywords*: *LTE-A, Wavelet Neural Network, Scheduling Rule, TTI.

I. INTRODUCTION

In this era of mobile data revolution, the users demand for the service and applications from mobile communication has gone far beyond the mere voice and telephony. The intensive growth in the services like web browsing, social networking, music and video streaming etc have driven the desperate requirement of the next generation of wireless standards. Keeping future cellular communications in view, the Third Generation Partnership Project (3GPP) was started to work in this area to meet the respective needs [1]. Release 8 of 3GPP has nominated this level of wireless standard as Long Term Evolution (LTE), which is also an important step to initiate towards 4th generation standard in cellular communication [2]. In comparison to the wireless mobile communication technologies like Global System for Mobile communications (GSM) (2G), General Packet Radio Service (GPRS) (2.5G), Enhanced Data rates for GSM Evolution (EDGE) (2.75G), Universal Mobile Telecommunications System (UMTS) (3G), High Speed Packet Access (HSPA) (3.5G), LTE (3.9G) provides better solutions for need of increased bandwidth for mobile applications and improves Radio Resource Management (RRM) process [1].

LTE and LTE-A are the latest mobile communication standards which has provided a transformative change in the evolution of mobile technology. The advanced standards have changed the complete infrastructure and architecture of the mobile networks. With a goal of improving spectral efficiency, systems capacity, coverage, flexible bandwidth operation, low latency, and many technological changes have been made in the network architecture. Various multiple access technologies like Code Division Multiple Access (CDMA), Orthogonal Frequency Division Multiple Access (OFDMA), Time Division Multiple Access (TDMA) have made the data intensive multimedia applications possible through mobile communication. The application of these aggressive technologies at physical and media Access control layer has made it possible to provide the intelligent management of radio resources. Radio resource management (RRM) performs the task of transmission power management, mobility management and the resource scheduling. Resource scheduling or packet scheduling has a great impact on the performance of the LTE network in terms the capacity, throughput, latency and spectral efficiency. It is a process of efficiently assigning the radio resources to each user on the basis of the requested service and required QoS. As the scheduling decision is taken by the Channel Quality Indicator (CQI) manager, Link Adaptation (LA) unit and Hybrid-Automatic Repeat request (H-ARQ) module, the complexity level of the process is considerably high [3-4].

The effect of scheduling decision on the overall system performance has attracted many researchers over the last few years to address the problem of intelligent decision making. D. Vinella and M. Polignano [5] proposed various packet scheduling schemes on the basis of user requirement and signaling information. They have proposed the dynamic, persistent and semi-persistent packet scheduling strategies and compared their performances for various real time applications. J. Song et. al. [6] proposed an energy efficient packet scheduling scheme for LTE downlink. They have presented a novel technique to decide the packet scheduling scheme with minimum transmit power. The proposed technique was compared with the round robin scheduling method and the performance was evaluated in terms of cell throughput and fairness for a minimum transmits power.

Manuscript published on 30 September 2019
* Correspondence Author
Hashim Ali*, Electronics and Communication, Dr. A. P. J. Abdul Kalam University , Indore,India. Email: hashim.sayed@gmail.com
Santosh Pawar, Electronics and Communication, Dr. A.P. J. Abdul Kalam University, Indore, India. Email: spawarrkdf@gmail.com
Manish Sharma, Electronics and Telecommunication, D Y Patil College of Engineering, Pune, India. Email: manishsharma.mitm@gmail.com

M. Aydin et.al. [7] proposed a multi user scheduling with simulated annealing. The opportunistic scheduler presented in this work identifies channel aware scheduling policies by maximizing the throughput. The frequency domain scheduling was proposed by S. Lee et. al [8] using full and half channel feedbacks. They have used Spatial Division Multiplexing with MIMO techniques and established a trade-off between throughput and signaling overhead. Genetic algorithm based packet scheduling schemes were proposed by Nan Zhou et.al.

[9] for the cross layer resource scheduling. They have referred the heterogeneous traffic for OFDM network. The cross layer packet scheduling is compared with sequential linear approximation algorithm on the basis of system capacity, throughput and traffic delay and found the cross layer scheme superior.

Ioan Sorin Comsa et.al [10] introduced a novel dynamic Q learning based scheduler technique using neural networks. By use of static values at threshold for throughput which are independent of network conditions which can makes scheduler inflexible for different trade-off levels are necessary. This work describes a dynamic scheduling algorithm which provides flexible results thus offers optimal solutions with respect to Channel Quality Indicator (CQI) for various user classes. This technique makes use of neural network to define appropriate scheduling rules for each state. Chun-Gui Li et. al. [11] presented a multi agent reinforcement learning using actor critic architecture. For realization of agent value temporal best response strategy is used. This work uses linear programming which computes Q-learning values. Actor-critic method has two metrics, one is to select action in less time period and second one is to learn policy.

To enhance the spectral efficiency and optimized resource utilization, the knowledge of parameters affecting the overall communication like electromagnetic environment, reliability of communication and the user requirements could be of great use. This can immensely improve the ICIC performance through the cognitive or self organizing behavior with the augmentation of artificial intelligence tools. Such an effort was made by A. Attar et al [12] by proposing a cognitive base station for efficient interference management for LTE. The proposed cognitive based station allocates the resources on the basis of the knowledge of the radio environment. The performance of the system was subject to the good learning capability and training data. The problem of efficient cognitive engine has been addressed by H. I. Volos and R. M. Buehrer [13] in terms of training speed, computational complexity and accurate learning. The overall performance of cognitive engine depends on the vastness of the training data because the system will behave uncertain while testing, in case of getting something which it is not trained for. The only solution to this problem is to train the CE with all the possible data. Keeping the randomness of the communication environment, it is practically impossible to explore all possible conditions as a priori. Also the retraining of CE for every random data leads to high energy and power cost. This methodology will found to be very risky if the radio is operating in a critical mission. This leads to the requirement of a system with long term learning capability and adaptability with the changing environment.

Neural network has been used by some researchers for the cognitivity [14-17] but the limitations of neural network in providing long term learning along with fast decision making and lesser complexity has made it a conservative solution for the problem of cognitive engine. The packet scheduling intelligence level has been improved by using NN as compared to the conventional technique. However, the NN has certain issues with limit its performance in dynamic and random environments. The basis function of NN is not orthogonal and redundant due to which its representation is neither unique not the most efficient one [18-19]. Also the convergence performance of NN for such systems cannot be guaranteed because they may reach to the local minima and get stuck there depending on the initial conditions. The limitations of the neural network have been addressed by many researchers and it was proposed that by replacing the basis function of neural network (Sigmoid) by wavelet, the performance can immensely be improved. The space and frequency localization property of wavelets found to be a very important characteristic of these networks known as Wavelet Neural network (WNN). This property has made the WNN superior than the conventional NN in terms of learning capability and convergence rate. WNN combines decomposition and identification ability of wavelet with the learning ability of NN architecture [20-23].

This paper deals with the designing of a smart decision making algorithm for the radio resource management for LTE-A using wavelet neural network. The proposed WNN is trained in the LTE environment to decide the proper scheduling rule to provide a spectrally efficient packet scheduling and to enhance the overall throughput of the system. The paper is organized as follows: system preliminaries and system description are addressed in section II and section III respectively. Section IV discusses WNN based packet scheduling in LTE-A. Simulation analysis of the proposed technique in LTE environment is presented in section V to verify its effectiveness while the paper is concluded in section VI.

II. SYSTEM PRELIMINARIES

A. Wavelet Neural Network

Owing to the universal approximation property, Neural Network (NN) has emerged as one of the most efficient approximation tools over the last two decades. The multi layer perceptron architecture of the neural network has enhanced the learning and decision making capabilities of the neural network. Still the network is prone to some malfunction and inaccurate performance because of its non orthogonal and redundant basis function which results in network architecture which is not unique and efficient. Though it has proved to follow a convergence rate while training, it may suffer from the problem of getting trapped in local minima for different initial conditions[20-23]. This may lead to the approximation error and degraded training performances.

To overcome these drawbacks of conventional neural network architecture, Zhang and Benveniste proposed wavelet networks, which is a novel architecture wavelet function as activation function instead of sigmoid function. It is a feed forward network with optimized position and dilation of the wavelets over the weights at the layer of neural network architecture. The learning capabilities of this network are improved because of the space and frequency localization property of wavelets and that too in lesser number of iterations as compared to conventional Neural networks. Wavelet networks have also established themselves as asymptotic optimal approximating algorithm for uncertain mathematical models.

They also require the minimum memory space to reconstruct an uncertain function within a specified precision [21].

Thus, proving the superior estimation performance of WNN based estimation over NN based estimation systems. The architecture of the WNN is shown in figure 1. It is a four layer structure which can be viewed as a network with an input vector, a layer of weighted multidimensional wavelets, a product layer and a linear output neuron. The coefficients of the linear part of the networks will be called direct connections.

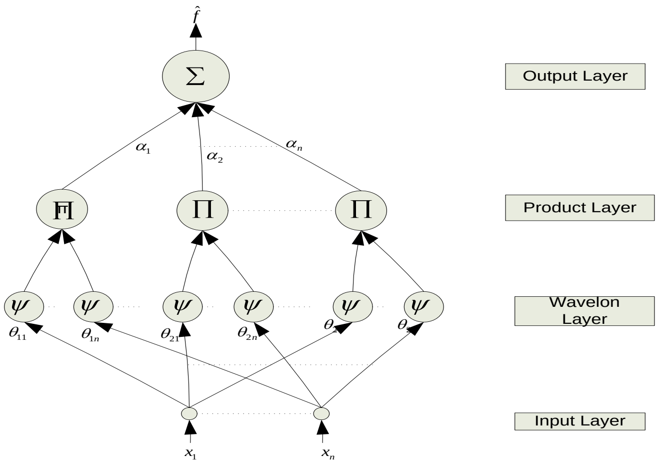

Fig. 1. Architecture of conventional WNN

B. LTE (Releases 8 and 9)

Third generation partnership project (3GPP) presented the first release of LTE standard in 2005. OFDM in downlink and SC-FDMA in uplink was proposed to be the technologies capable of delivering the requirement set of LTE standard. Various MIMO configurations were included later for the higher versions in the subsequent years. Release 8 and 9 included some minor enhancements like multimedia Broadcast / Multicast Services (MBMS) support, location services, base stations with multiple standards support.[24]

C. LTE-Advanced (Release 10)

All Addition of some advanced techniques like carrier aggregation, enhanced downlink MIMO, relays etc, in the original LTE standards has resulted in the release of an evolution named LTE Advanced. LTE-A was released in December 2010. Long Term Evolution-Advanced (LTE-Advanced) is a standard used for high speed cellular applications and is a step forward to Long Term Evolution (LTE) standard. It is a new network technology that is expected to give better coverage, greater stability, and faster performance. As compared to previous technologies, such as Global GSM/EDGE and UMTS/HSxPA, LTE provides enhanced performance. The LTE radio access network, offers important benefits for users and operators such as high performance and capacity, flexibility, self-configuration and self-optimization, improved cell capacity, reduced latency and mobility. Significant variations in the instantaneous channel conditions however, severely affect the overall performance of the mobile network. This requires an efficient resource management in the overall architecture of LTE advanced to handle the power, mobility and spectral characteristics [25].

D. Radio Resource Scheduling/ Packet Scheduling

Packet scheduling, transmission power management, and the mobility management is taken care through the Radio resource management block of LTE advanced architecture. This governs the overall spectral efficiency of the network and the optimal utilization of the radio resources. The radio resources are assigned to each user through packet scheduling as per the requested service by the user for every TTI as per the scheduling rule. The capacity, stability, QoS, user fairness and spectral efficiency are the major parameters which are especially been taken care by packet scheduler. A proper trade off is always maintained in these parameters through the scheduler [26].

However, the implementation of one uniform rule for the whole scheduling process does not result into an efficient trade off. This is due to the suitability of various scheduling rule for various environmental situations for every TTI. The mixture of various rules for different TTI and its respective environmental conditions has proved to be an efficient way to achieve the desirable compromise between various performance metric of the LTE network. This results in the improvement in throughput, system capacity and spectral efficiency.

III. SYSTEM DESCRIPTION

This The general LTE packet scheduler framework is shown in fig 2. The task of packet scheduler is to assign the scheduling rule for various resources at each TTI. The packets are maintained in a queue and depending on the scheduling metric and other control parameters, the scheduler generates the output. The factors governing the scheduling process are as follows:

- Channel quality information (CQI) reports—This carries the information about the channel conditions for each UE and provide it to the UE in order to provide an efficient scheduling priority according to a given value.
- Hybrid automatic repeat request (H-ARQ) retransmission—It distinguishes between PRBs that should be either retransmitted or dedicated as a new transmission.
- The history of UE’s transmission.
- Allowed number of UEs that can be accepted in each TTI.

- Adjacent PRB allocation constraints in terms of uplink scheduling. Due to the SCFDMA, the PRBs assigned to a particular UE must be contiguous in the frequency domain

  The RRM offers different scheduling rule for each TTI which is set to be 1ms long. Assume that M users are allocated with N resources at the start of each TTI. Allotment of rule at the start of each TTI for each user on the basis of various parameters is a very complex problem and requires a policy framework. It should be done on the basis of some predefined policy which considers the entire

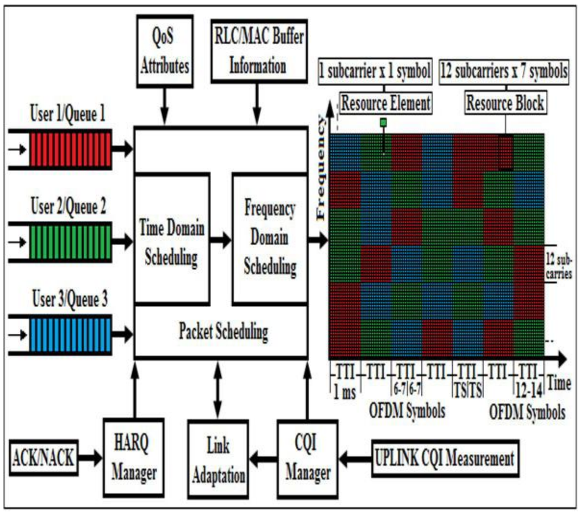

Fig. 2. LTE packet scheduler framework [10]

possible environmental situation while allocating a rule. Considering r number of rules for p number of TTIs with the following distribution

$$R_i \in R = \{R_0, R_1, R_2, \ldots, R_{r-1}\}$$

$$TTI_j \in TTI = \{TTI_0, TTI_1, TTI_2, \ldots, TTI_{r-1}\}$$

Then, the policy p_k. can be defined as:

$$p_k = \{R_0, R_1, R_2, \ldots, R_{r-1}\}$$

Each rule in the rules set represents an action which resembles to a state in the TTI matrix having S columns (symbols) and N radio resources (subcarriers). The TTI matrix represents the mapping of selected rule for a certain state. By performing an action $R_i \in R$ the agent will move from one state TTI_{i-1} to another state TTI_i. This transition needs an intelligent scheduling for the efficient resource management.

IV. PROPOSED METHODOLOGY

The intelligence in the packet scheduling algorithm is added through the wavelet neural network based decision making for the allocation of scheduling rule for each TTI. This proposed network is trained using the input parameters and target values. The trained network is then deployed into LTE scheduler for proper scheduling of radio resources which can be assigned to users. This system has some advantages like increased efficiency and reduced complexity with the minimum calculations and processing time. The input parameters for the proposed system are channel parameters like SNR, BLER, Sector SINR with shadowing effect, Sector SINR without shadowing effect, CQI, power and bandwidth. The packet scheduling rules considered are Round robin, Proportional Fair (PF), Exponential/Proportional Fair (EXP/PF), Exponential (EXP) Rule, Maximum Largest Weighted Delay First (M-LWDF), Logarithmic (LOG) Rule and Frame Level Scheduler (FLS) LTE downlink packet scheduling, Best CQI scheduler.

Figure 3 shows a block diagram representing flow of overview of proposed LTE scheduling system. Wavelet neural network is designed and implemented in this work to provide an intelligent resource allocation strategy by selecting the best possible scheduling rule. WNN has

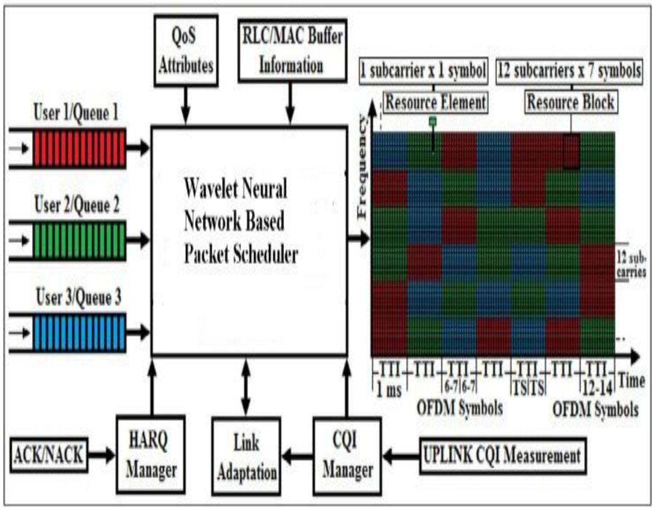

Fig. 3. WNN based LTE packet scheduler framework

successfully been applied over the variety of applications including signal processing, control system, time series analysis, functional estimation over the last two decades. However, it has never been applied to the scheduling in any wireless technology so far to the best of the knowledge of the authors. The accurate run time decision making is performed using the efficient training process of the neural network.

V. WNN BASED LTE PACKET SCHEDULER FRAMEWORK

The effectiveness of WNN is governed by the optimal designing of the wavelet layer of the network which comprises of translated and dilated versions of orthonormal wavelet function and the respective basis function lies within the $L^2(\Re)$ subspace to represent a function $f(x) \in L^2(\Re)$ appoximated by linear combination of basis functions, where the whole space S can be represented as[20]

$$S = S_i \oplus W_i \oplus W_{i-1} \oplus W_{i-2} \cdots \oplus W_0 \oplus W_{-1} \cdots \quad (1)$$

The dyadic translation and binary dilation of $\phi \in S$ and $\varphi \in S$ generates the wavelet bases represented as

$$\phi_{jq}(x) = 2^{j/2}\phi(2^j x - q) \qquad j, q \in Z$$

$$S_j = span\{\phi_{jq}(x), q \in Z\}$$

and

Retrieval Number C4866098319/2019©BEIESP
DOI: 10.35940/ijrte.C4866.098319
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

$$\varphi_{jq}(x)=2^{j/2}\varphi(2^{j}x-q) \qquad j,q\in Z$$
$$W_j=span\left\{\varphi_{jq}(x),q\in Z\right\}$$

The wavelet series expansion can be used to represent any function $f(x(k))$ in space S as

$$f(x(k))=\sum_{j=N1}^{N2}\sum_{q=M1}^{M2}\left\langle\phi_{j,q}(x(k)),f(x(k))\right\rangle\phi_{j,q}(x(k)) \quad (2)$$

where

$$\lim_{\substack{N1,M1\to-\infty\\N2,M2\to+\infty}}\left\|f(x(k))-\sum_{j=N1}^{N2}\sum_{k=M1}^{M2}\left\langle\varphi_{j,q}(x(k)),f(x(k))\right\rangle\varphi_{j,q}(x(k))\right\|=0$$

Truncation of the wavelet series is done to attain the finite number of translations and dilations at each resolution which transform (2) in

$$f(x(k))=\sum_{j\geq J}^{N}\sum_{q=M1_j}^{M2_j}\left\langle\phi_{j,q}(x(k)),f(x(k))\right\rangle\phi_{j,q}(x(k))+\varepsilon(x(k)) \quad (3)$$

where j is lowest resolution, $N\in\Re$ represents the highest resolution while $q=\left[M1_j,\cdots,M2_j\right]\in\Re$ represents the number of translates at j^{th} resolution and $\varepsilon(x(k))$ is the approximation error defined as

$$\varepsilon(x(k))=f(x(k))-\sum_{j\geq J}^{N}\sum_{q=M1_j}^{M2_j}\left\langle\varphi_{j,q}(x(k)),f(x(k))\right\rangle\varphi_{j,q}(x(k)) \quad (4)$$

Applying the property of multi resolution analysis on (3) results

$$f((x(k)))=\left\{\begin{array}{l}\sum_{q=M1_J}^{M2_J}\left\langle\phi_{J,q}(x(k)),f(x(k))\right\rangle\phi_{J,q}(x(k))+\\ \sum_{j\geq J}^{N}\sum_{q=M1_j}^{M2_j}\left\langle\varphi_{j,q}(x(k)),f(x(k))\right\rangle\varphi_{j,q}(x(k))+\varepsilon(x(k))\end{array}\right\} \quad (5)$$

Tensor product of single dimensional wavelet for $f(x(k)):\Re^n\to\Re$ to derive the extended multidimensional wavelet network as,

$$\phi_{J,q}(x(k))=\prod_{i=1}^{n}\phi_{J,q}(x_i(k));\quad \varphi_{j,q}(x(k))=\prod_{i=1}^{n}\varphi_{j,q}(x_i(k)) \quad (6)$$

$$f(x(k))=\left\{\begin{array}{l}\sum_{q=M1_J}^{M2_J}\left\langle\phi_{J,q}(x(k)),f(x(k))\right\rangle\phi_{J,q}(x(k))+\\ \sum_{j\geq J}^{N}\sum_{q=M1_j}^{M2_j}\left\langle\varphi_{j,q}(x(k)),f(x(k))\right\rangle\varphi_{j,q}(x(k))+\varepsilon(x(k))\end{array}\right\}$$
$$=\sum_{q=M1_J}^{M2_J}\alpha_{J,q}(k)\phi_{J,q}(x(k))+\sum_{j\geq J}^{N}\sum_{q=M1_j}^{M2_j}\beta_{j,q}(k)\varphi_{j,q}(x(k))+\varepsilon(x(k)) \quad (7)$$

where $\alpha_{J,q}(k)$ $\beta_{j,q}(k)$ are defining the weights of wavelet basis functions. Rewriting (7) as

$$f(x(k))=\alpha^T(k)\phi(x(k))+\beta^T(k)\varphi(x(k))+\varepsilon(x(k)) \quad (8)$$

where

$\alpha(k)=\left[\alpha_{JM1_J}(k),..,\alpha_{JM2_J}(k)\right]^T$ and

$\beta(k)=\left[\beta_{JM1_J}(k),\cdots,\beta_{JM2_J}(k),\cdots,\beta_{NM1_N}(k),\cdots\beta_{NM2_N}(k)\right]^T$

are the scaling and wavelet weight vectors respectively. Wavelet and scaling vectors denoted as

$$\varphi(x(k))=\begin{bmatrix}\varphi_{JM1_J}(x(k)),\cdots,\varphi_{JM2_J}(x(k)),\cdots\\ \cdots,\varphi_{NM1_N}(x(k)),\cdots,\varphi_{NM2_N}(x(k))\end{bmatrix}^T$$

and $\phi(x(k))=\left[\phi_{JM1_J}(x(k)),..,\phi_{JM2_J}(x(k))\right]^T$ respectively.

Equation (8) can be represented for a constant $\lambda>0$ and optimal weights vectors α^*,β^* as :

$$f(x(k))=\left\{\begin{array}{l}\sum_{q=M1_J}^{M2_J}\alpha^*_{J,q}(k)\phi_{J,q}(x(k))+\sum_{j\geq J}^{J_N}\sum_{q=M1_j}^{M2_j}\beta^*_{j,q}(k)\varphi_{j,q}(x(k))\\ +\varepsilon(x(k))\end{array}\right\}$$
$$=\alpha^{*T}\phi(x(k))+\beta^{*T}\varphi(x(k))+\varepsilon(x(k))\ \forall x(k)\in\Omega\subset\Re^n \quad (9)$$

where Ω is a compact set and $\varepsilon(x(k))$ is assumed to be $|\varepsilon(x(k))|\leq\lambda$. Also,

$$\hat{f}(x(k))=\hat{\alpha}^T\phi(x(k))+\hat{\beta}^T\varphi(x(k)) \quad (10)$$

where $\hat{\alpha},\hat{\beta}$ are the estimated values of α^*,β^* respectively. The estimation error may be represented as

$$\tilde{f}(x(k))=f(x(k))-\hat{f}(x(k))=$$
$$\left\{\tilde{\alpha}^T(k)\phi(x(k))+\tilde{\beta}^T(k)\varphi(x(k))+\varepsilon(x(k))\right\} \quad (11)$$

where $\tilde{\alpha}(k)=\alpha^*-\hat{\alpha}(k),\tilde{\beta}(k)=\beta^*-\hat{\beta}(k)$

Proper selection of number of resolutions can minimize the estimation error such that the bound $\left\|\tilde{f}(x(k))\right\|\leq\tilde{f}_m$ holds for all $x\in\Omega\subset\Re^n$. The weights of WNN can be adaptively tuned by the gradient descent algorithm by minimizing the least square cost function:

$$J(\theta)=\frac{1}{2}\sum_{n=1}^{N}(y_p^n-y^n)^2 \quad (12)$$

where the cost function $J(\theta)$ explicitly depends upon the weights of the connections between wavelets and the output. Using the backpropagation algorithm the weight updating rule can be expressed as

$$w(k+1) = w(k) + \Delta w(k) = w(k) + \eta\left(-\frac{\partial E(k)}{\partial w(k)}\right) \tag{13}$$

where η and w representation the learning rate and the tuning weights respectively. Using the framework of wavelet neural network, the scheduler is trained for the efficient scheduling in the dynamic and random environment. The adaptive nature of the WNN to this system makes a efficient solution for the radio resource management for the large wireless mobile network of the scale of LTE-A.

VI. RESULTS AND DISCUSSION

The simulation study and performance evaluation of proposed system is conducted under MATLAB environment and the experiment is performed over the LTE system-level simulator [27,28].

All the parameters assumed for basic LTE system model are having same initializations that are made by 3GPP for LTE. The data files included in the system contains all required configuration parameters, environmental measurements and performance metric statistics. Also parameters required for training purpose of neural network are extracted from the modeled LTE system. Training and validation of neural network is also performed in MATLAB. Parameters required for the training of WNN are extracted from LTE system model. The training and validation of this network is done with the dataset having 500 samples as inputs and target. A subset of this data is used for training purpose and remaining data is used for comparison and performance prediction of trained neural network. The input parameters for the proposed system are channel parameters like SNR, BLER, Sector SINR with shadowing effect, Sector SINR without shadowing effect, CQI, power and bandwidth. The packet scheduling rules considered are Round robin, Proportional Fair (PF), Exponential/Proportional Fair (EXP/PF), Exponential (EXP) Rule, Maximum Largest Weighted Delay First (M-LWDF), Logarithmic (LOG) Rule and Frame Level Scheduler (FLS) LTE downlink packet scheduling, Best CQI scheduler. The simulation parameters are as given in table 1.

Table 1: Simulation parameters

Parameters	Value/description
Carrier Frequency	2 GHz
Bandwidth	5 MHz
Number of Sub-carriers	300
Number of RBs	25
Number of Sub-carriers per RB	12
Sub-carrier Spacing	15 kHz
Slot duration	0.5 ms
Scheduling Time (TTI)	1 ms
Number of OFDM Symbols per Slot	7
Multipath	Jakes model
Shadowing:	log- normal distribution (mean = 0 dB, σ = 8 db)
Carrier Frequency	2 GHz
Frame structure	FDD
Bandwidth	10 MHz
Number of RBs	50
Subcarriers per RB	12
Subcarrier spacing	15 kHz
Resource block	180 kHz
Download power transmission	43 dBm (equally distributed among RBs)

With an objective to estimate the best possible packet scheduling rule in an optimal manner and to minimize the mean square value of estimation error, WNN architecture is proposed in this work. To construct the WNN architecture, discrete Shannon's wavelet is used, which possesses so many attractive features like orthonormality, multiresolution etc. The network used here is composed of 3 nodes. The tuning laws for the wavelet network are derived using gradient descent algorithm as addressed earlier. The simulation is carried out over a time span of 60 seconds with a mean square value of tracking error about 2×10^{-4}. Owing to the efficient scheduling rule estimation on the basis of the environmental parameters by proposed strategy, the system shows a promising performance. The performance of the overall LTE system after implementing the proposed WNN based scheduler is shown in the subsequent figures.

Figure 4 shows the LTE Block Error Rate (BLER) variation with respect to different Signal to Noise Ratio (SNR) for various Channel Quality Indication (CQI) values for the proposed scheduler. In LTE eNodeB collects CQI, which is then used to determine the Modulation and Coding Scheme (MCS) for every UE in a cell. The CQI report of all UEs is received by the scheduler. These CQI reports are number between 0 (worst) and 15 (best) and it indicates the efficiency of MSC and gives BLER about 10% or less.

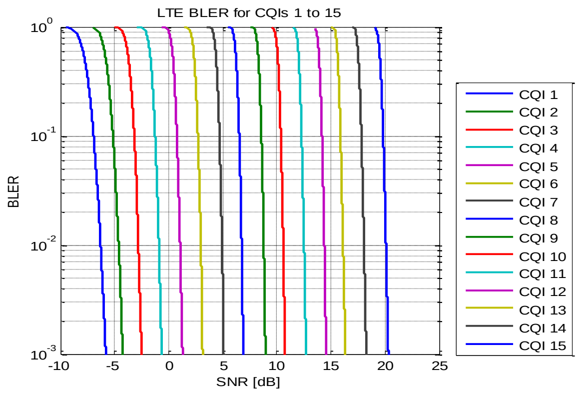

Fig. 4. LTE BLER for CQI 1 to 15

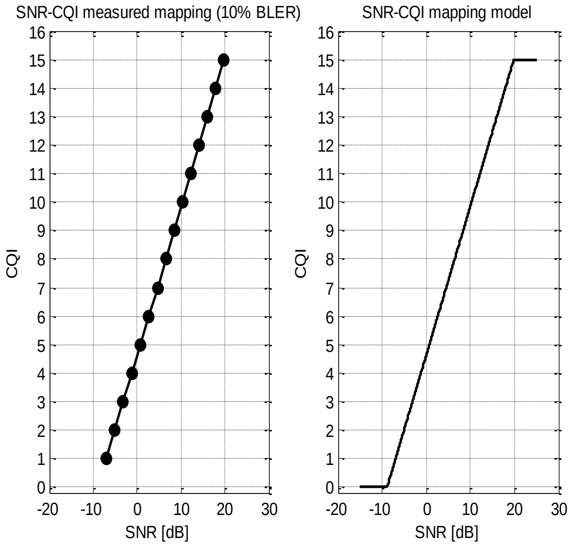

Fig. 5. SNR-CQR Mapping

Figure 5 represents the SNR-CQI mapping, SNR (db) and CQI are mapped with respect to CQI reports of all UEs and this mapping changes according to type of channel. In the above mapping 10% BLER is considered which is calculated from CQI reports numbered from 1 to 15. The mapping is observed to be in increasing manner with respect to BLER value of 10%.

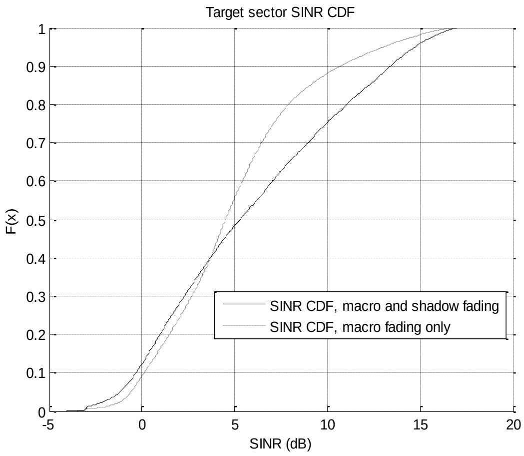

Fig. 6. Target sector SINR CDF

Cumulative Distribution Function (CDF) for Signal-to-Interference-plus-Noise Ratio (SINR) is measured and is shown in Figure 6 for the proposed system. The target sector SINR CDF represents the mobility effect on SINR under various environments i.e. for combined effect of macro and shadow fading and for macro fading only. Macro fading is due to antennas which are situated at different access points or base station. And shadow fading is due to shadowing from any obstacle which affects wave propagation. The aim is to reduce these fading effects and to increase signal strength and signal quality of the received signal.

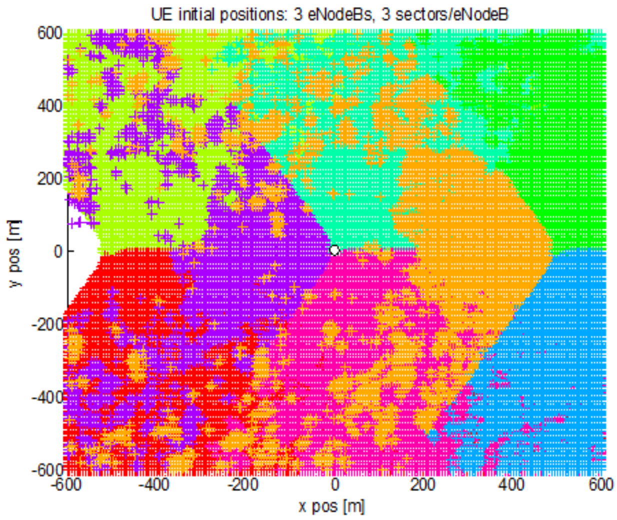

Fig. 7. Initial position of UE

Figure 7 indicates a point of initial position of UE. UE positioning is basically used to determine the geographical position of UEs. This UE positioning function is required for services which are based on location and also for scheduling of resources in radio resource management.

VII. CONCLUSION

In the proposed system, Scheduling of radio resources in LTE environment has been performed. Schedulers are assigned with different scheduling rules and scheduler selects the appropriate rule at each TTI. The selection is carried out in minimum time period with the help of wavelet neural network mechanism along with reinforcement learning based actor-critic algorithm. Use of WNN mechanism provides advantage of improved prediction capabilities and advantage of reduced processing time and reduced complexity with better results. Thus in the proposed system, by considering all the results obtained through WNN, radio resource scheduling process in LTE is carried out in more efficient way in less processing time period.

REFERENCES

1. Tshiteya Dikamba, "Downlink Scheduling in 3GPP Long Term Evolution (LTE)" Assignment of Master of Science Thesis, Delf University of Technology, March 2011.
2. Sajid Hussain, "Dynamic Radio Resource Management in 3GPP LTE" thesis of Master of Science in Electrical Engineering, Blekinge Institute of Technology, pp. 11-45, January 2009.
3. Mehmet E. Aydin, Raymond Kwan, Wei Ding and Joyce Wu, "A Genetic Algorithm Approach for Multiuser Scheduling on the LTE Downlink" in Proceedings of the World Congress on Engineering, Vol. 2, pp.1252-1257,July 2012.
4. P. K. Agyapong, M. Iwamura, D. Staehle, W. Kiess and A. Benjebbour, "Design considerations for a 5G network architecture," IEEE Communications Magazine, vol. 11, pp. 65–77, Nov. 2014.
5. D. Vinella and M. Polignano, "Discontinuous reception and transmission (DRX/DTX) strategies in Long Term Evolution (LTE) for voice-over-IP traffic under both full dynamic and semi-persistent packet scheduling policies", Aalborg University, November 20th, 2009.
6. J. Song, G.T. Gil and D.H. Kim, "Packet-scheduling algorithm by the ratio of transmit power to the transmission bits in 3GPP LTE downlink", EURASIP Journal on Wireless Communications and Networking, pp. 1-8, July, 2011.

7. M. Aydin, R. Kwan, J. Wu and J. Zhang, “Multiuser Scheduling on the LTE Downlink with Simulated Annealing”, in VTC2011 Spring Budapest, May, 2011.
8. S. Lee, S. Choudhury, A. Khoshnevis, S. Xu and S. Lu, “Downlink MIMO with frequency-domain packet scheduling for 3GPP LTE”, in the proceedings of IEEE INFOCOM, 2009.
9. Nan Zhou, Xu Zhu and Yi Huang, “Genetic algorithm based cross-layer resource allocation for wireless OFDM networks with heterogeneous traffic”, in the 17th European Signal Processing Conference, Glasgow, August, 2009.
10. Ioan S. Comşa, M. Aydin, S. Zhang, P. Kuonen and Jean–Frederic Wagen, “Reinforcement Learning based Radio Resource Scheduling in LTE-Advanced”, IEEE 17th international conference on Automation & Computing, pp. 219-224, January 2011.
11. Chun-gui li, Meng Wang and Qing-neng Yuan, “A Multi-Agent Reinforcement Learning Using actor-Critic Methods”, 7th International Conference on Machine Learning and Cybernetics, vol. 2, pp. 878-882, September 2008.
12. A. Attar, V. Krishnamurthy and O. N. Gharehshiran, “Interference management using cognitive base-stations for UMTS LTE” , IEEE Communications Magazine, vol. 49, no. 8, pp. 152–159, 2011.
13. H. I. Volos and R. M. Buehrer, “Cognitive radio engine training,” Wireless Communications, IEEE Transactions on, vol. 11, no. 11, pp. 3878–3889, 2012.
14. A. Adeel, H. Larijani and A. Ahmadinia, “Performance analysis of random neural networks in LTE-UL of a cognitive radio system,” in 1st IEEE International Workshop on Cognitive Cellular Systems, IEEE CCS 2014, Rhine River, Germany, Sept 2-4, 2014.
15. Adeel, H. Larijani and A. Ahmadinia, “Efficient use of random neural networks for cognitive radio system in LTE-UL,” in in Proc. IEEE International Symposium on Wireless Communication Systems, ISWCS 2014, Barcelona, Spain, August 26-29, 2014.
16. A. Adeel, H. Larijani, A. Javed and A. Ahmadinia, “Critical analysis of learning algorithms in random neural network based cognitive engine for LTE systems,” in IEEE Vehicular Technology Conference (VTC), 2015.
17. A. Adeel, H. Larijani, A. Javed and A. Ahmadinia, “Random neural network based power controller for inter-cell interference coordination in LTE-UL,” in IEEE ICC 2015 Workshop on Advances in Software Defined and Context Aware Cognitive Networks, 2015.
18. J. Zhang, Gilbert *G.* Walter, Y. Miao and W. Lee, “Wavelet Neural Networks for Function Learning”, IEEE transactions on signal processing, vol. 43, pp.1485-1497, June 1995.
19. David Veitch, “Wavelet Neural Networks and their application in the study of dynamical systems”, Dissertation in University of York UK, August 2005.
20. Q. Zhang and A. Benveniste, “Wavelet networks” , IEEE Transactions on Neural Networks, Vol. 3, no. 6, pp.889-898, November 1992.
21. J. Zhang, G. G. Walter, Y. Miao and W. Lee, “Wavelet neural networks for function learning,” IEEE Transactions on Signal Processing, Vol. 43, no. 6, pp.1485-1497, June 1995.
22. Hussein Jaddu and Kunihiko Hiraishi, “A Wavelet Approach for Solving linear quadratic optimal control problems”, SICE-ICASE International Joint Conference ,Oct. 18-21, Korea, 2006.
23. K. K. Minu, M. C. Lineesh and C. Jessy John, “Wavelet Neural Networks for Nonlinear Time Series Analysis”, Applied Mathematical Sciences, Vol. 4, 2485 – 2495, 2010.
24. Ericsson, White Paper, “LTE – an introduction”, June, 2009.
25. Motorola, White Paper, “Long Term Evolution: A Technical Overview”.
26. S. Hussain, “Dynamic Radio Resource Management in 3GPP LTE”, Blekinge Institute of Technology, January, 2009, pp. 11-45.
27. [Online]Available: http://www.nt.tuwien.ac.at/ltesimulator/
28. C. Mehlfuhrer, M. Wrulich, J. C. Ikuno, D. Bosanska, and M. Rupp, ¨ “Simulating the long term evolution physical layer,” in Proc. of the 17th European Signal Processing Conference (EUSIPCO 2009), Glasgow, Scotland, Aug. 2009.

AUTHORS PROFILE

Hashim Ali received the B.E. degree in Electronics engineering from RGPV University and the M.E. degree in Digital Instrumentation engineering in 2008 From DAVV University, Indore, India. Currently, he is Perusing PhD in DR. APJ Abdul Kalam University Indore. He has published 6 papers in National and international conferences. His research interests are in the area of signal processing and Wireless Communication and its applications, primarily in digital communications.

Dr. Santosh Pawar has received Doctor of Philosophy in the area of Non-Linear Fiber Optics from Devi Ahilya Vishwavidhyalaya, Indore in 2014 and Master of Technology in Optical Communication from Shri G. S. Institute of Technology and Science, Indore, in 2007.

His research area spans from wireless communication, optical fiber communication, integrated optics, non-linear optics, optical fiber Bragg grating based devices and optical wireless communication.

He has published more than 25 research papers in leading International Journals indexed in SCI, WOS and SCOPUS and presented around 30 research papers in International/National conferences. Under his supervision he guided 15 master’s thesis and 1 Ph.D. thesis. He his life member of Indian Science Congress Association (ISCA).

Dr. Manish Sharma has received Doctor of Philosophy in the area of Intelligent Control from Devi Ahilya Vishwavidhyalaya, Indore in 2014 and Master of Technology in Digital Instrumentation from IET, DAVV, Indore, in 2006.

His research area includes artificial Intelligence, Advanced wireless communication, optimization, Control theory and application, Machine learning. He has published more than 35 research papers in leading International Journals and presented around 30 research papers in International/National conferences.