DOWNLINK RESOURCE BLOCKS POSITIONING AND SCHEDULING IN LTE SYSTEMS EMPLOYING ADAPTIVE FRAMEWORKS

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ABSTRACT

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The expansions in size and complexity of LTE networks is hindering their performance and reliability. This hindrance is manifested in deteriorating performance in the User Equipment's throughput and latency as a consequence to deteriorating the E-node B downlink throughput. This leads to the need for smart E Node Base with various capabilities adapting to the changing communication environment. The proposed work aims at developing Self Organization (SO) techniques and frameworks for LTE networks at the Resource Block (RB) scheduling management level. After reviewing the existing literature on Self Organization techniques and scheduling strategies that have been recently implemented in other wireless networks, we identify several critical needs that can jointly be addressed. The deployment of the introduced algorithms in the communication network is expected to lead to improved and upgraded overall network performance.

The main feature of the LTE network family is the feedback that the cell receives from the users. The feedback includes the down link channel assessment based on the User Equipment (UE) measure, namely the Channel Quality Indicator (CQI) in the previous Transmission Time Interval (TTI). This feedback should be the main decision factor in allocating Resource Blocks (RBs) among users. The challenge is to how one could map the users' data onto the RBs based on the CQI. The Thesis advances two approaches towards that end:

(i) The allocation among the current users for the next TTI should be mapped, consistent with the historical feedback CQI received from users over prior transmission durations. This approach also aims at offering a solution to the bottleneck capacity issue in the scheduling of LTE networks. To that end, we present an implementation of a modified Self Organizing Map (SOM) algorithm for mapping incoming data into RBs. Such an implementation can enable cells to become smarter. The criteria in measuring the E-node Base performance include throughput, fairness and the trade-off between these attributes.

(ii) Another promising and complementary approach is to tailor Recurrent Neural Networks (RNNs) to implement optimal dynamic mappings of the Resource Blocks (RBs) in response to the history sequence of the Channel Quality Indicator CQI feedback. RNNs can successfully build their own internal state over the entire training CQI sequence and consequently make the prediction more viable. With this dynamic mapping technique, the prediction is likely to be more accurate to changing time-varying channel environments.

Overall, the collective cell management would become more intelligent and would be adaptable to changing environments. Consequently, a significant performance improvement can be achieved at lower cost. Moreover, a general tunability of the scheduling system becomes possible which would incorporate a trade-off between system complexity and QoS.

To my parents, for their devotion and sacrifice,
To my siblings, for their help and encouragement,
To my friends, with whom I spent so many precious moments.
I dedicate my work,
Symbol of gratitude and love.

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KEY TO ABBREVIATIONS

AMC	Adaptive Modulation and Coding
BLER	Block Error Rate
BET	Blind Equal Throughput
CQI	Channel Quality Indicator
DCI	Downlink Control Information
eNB	evolved Node B
FDPS	Frequency Domain Packet Scheduler
FLS	Frame Level Scheduler
GBR	Guaranteed bit-rate
HARQ	Hybrid Automatic Retransmission Request
LTE	Long Term Evolution
LWDF	Modified LWDF
MCS	Modulation and Coding Scheme
MT	Maximum Throughput
OFDM	Orthogonal Freq. Division Multiplexing
OFDMA	Orthogonal Freq. Division Multiple Access
PDCCH	Physical Downlink Control Channel
PDSCH	Physical Downlink Shared Channel
PUSCH	Physical Uplink Shared Channel
PF	Proportional Fair
PLR	Packet Loss Rate

PSS	Priority Set Scheduler
QCI	QoS Class Identifier
QoS	Quality of Service
RB	Resource Block
RLC	Radio Link Control
RR	Round Robin
RRM	Radio Resource Management
SC-FDMA	Single Carrier Freq. Division Multiple Access
SGW	Serving Gateway
TDPS	Time Domain Packet Scheduler
TTA	Throughput To Average
TTI	Transmission Time Interval
UE	User Equipment
VPM	VoIP priority mode

Chapter 1. Introduction

1.1. Self-Organization in Technology:

In the last four years, LTE networks have undergone massive changes, updates and developments, because they are the best candidate to be the backbone network for 5G and beyond. The User behavior of the wireless system has had huge changes; this is supported by the observable growth of bandwidth demanding applications such as video streaming and multimedia file sharing. These developments have applied pressure on communication systems to increase capacity, Quality of Service (QoS), energy efficiency and the most significant aspects of these cellphone usage [43].

While, it is typical for any wireless communication system to be pressured by increased capacity demand, now this problem is further aggravated by financial constraints from the operator's point of view, because with higher capacity and QoS comes higher capital expenditure (capacity cost) and operating expenditure (operating cost). Since users may be reluctant to pay proportionally higher bills for improved services, minimizing Capacity Cost and Operating Cost will render the business model commercially viable. This will be a challenge in each new release of wireless networks as well as in the daily basic functionality. Thus, the tradeoff between providing improved services and retaining reasonable profits is the crucial consideration with which operators struggle.

Such challenges are among the main motivations for researchers seeking to bring autonomous intelligent adaptation techniques to the field. Mostly, these techniques are labeled Self Organization (SO), and the main motivating factors are:

- Optimal Capacity: the physical upper bound on the inherently unpredictable nature of spatio temporal dynamics process associated with wireless cellular systems. One seeks the optimal performance in terms of capacity and QoS which is not achievable with the current fixed legacy designs. In wireless communication systems the user mobility and the channel model variability are naturally the main reasons for the communication system suffering from resource under-utilization, expressed in low resource efficiency or over utilization, which results in low QoS as well as poor capacity [31]
- Small Cells: All new creative tools like Femto-Cell, Small Cells, out-door relays, In-door relays …etc that latest generations of wireless communication systems are using as the main tools toward improving the capacity and the QoS of indoors and special cases places. All of these updated (e-node Bs) lead to systems with a several nodes which will cause a lot of interference resulting in degradation for the neighboring macro cell (main E-Node B) if there are no Self Organizing techniques attached with all these femto/relays devices.
- Periodic Manual optimization is required and it should be in a classic approach, this is because the increased complexity of systems will lead to greater human errors which will result in longer recovery and restoration times, all this will have an effect especially with the huge scale of the wireless systems.
- Toward improving the operating expenses performance significantly as it eliminates the need for expensive skilled labor required for configuration, commissioning, optimization, maintenance, troubleshooting and recovery of the system.

For these issues and more it is clear Self Organizing SO is not only a feature toward future LTE networks like LTE-A and LTE-U, it will eventually become mandatory because of the scale of these networks and their standers.

Even though Self-Organizing is new in wireless communication networks technology, you can find some initial implementation of Self Organizing strategies in several types of wireless networks like Sensor networks, Ad hoc networks,... ,etc. As described in [9], [10] and [11], autonomic computer networks have been implementing the Self Organizing (SO). Making it rapidly growing area. Since this last decade, some researchers intend to focus on this domain. Below is a review of relevant literature and technical reports on the topic and contribution which provides a comprehensive description of the hierarchy and the development of this domain.

Here, I provide a consolidated review of recent developments on self-organization in communication systems on general characteristics solutions and the methodologies which are related to designing self-organization in cellular networks.

The Aim of this literature review is to identify potential methodologies and the open research issues for designing Self Organizing SO in future systems. In this process, we also discuss a set of important features that make an algorithm or system self-organizing.

In this chapter, we provide a firm definition and understanding of the term Self Organization and its specialty. We start with definitions used in other disciplines, then we deduce the adaptive, autonomous and learning methods which are keys in defining such systems. Furthermore, we elaborate on stability, scalability and agility as characteristics that are desired most in any Self Organized systems. As such, a system exhibiting any of these characteristics is considered as having some form of intelligence. We provide a better understanding on the difference and similarities between adaptive systems, autonomous systems, cognitive networks and self-organized networks [117] [119].

1.1.1. Definition of Self-Organization

Even Self-Organization is a technological concept named by many different of implementations. But, the main Inspiration of Self Organization is from Artificial Neural Network ANN, as the concept is one of the main topics in the field, where certain biological systems exhibit unique organized behavior in order to achieve a desired objective. This was with autonomously and intelligently adopting to dynamics of their immediate environment. So, Self-Organizing is result of unsupervised learning on Artificial Neural Network ANN [120] [121] [123].

Biological unsupervised Learning: Generally, in biological type networks there are not a lot of different learning methodologies for unsupervised learning and supervised learning. Most connections between visual cortical areas are two-way bottom up from the retina and top-down from later areas, where the final destination of signals are the motor areas. Self-Organization (SO) is considered as unsupervised learning by computer science and cybernetics [12].

Talking about SO in communication systems, in [13] they defined SO as Cognitive Dynamic systems of future cellular systems. An intelligent system such as this would learn from the environment and adapt to statistical variations in input stimuli toward achieving highly reliable communications whenever and wherever needed. This means Self Organizing (SO) is an adaptive functionality. So, the network can detect changes and based on these changes make intelligent decisions to minimize or maximize the effect of those changes as [14] defined. These explanations are understood from the biological beliefs such: The effects of the unsupervised learning like SO biases development. So, the features derived and the organization of the earlier layers is more effective for task performance. Global convergence of patterns appears at the motor level (base layer), while sub-pattern “soft” convergence appear at earlier levels. These soft-convergence representations can be useful for more than one category (multipurpose). The final representation (features) and organization are selective – or motor-biased, which does not have to be task-specific because, task-specific representation is "greedy" in the sense that it discards as much information as possible that is not required for the current task. The following chapters we will explain more of the benefits of non-task-specific learning [110] [112] [125]. Proffered features of SO for wireless networks are the primitive concept of Artificial Neural Network ANN like adaptability, dynamic and emergent behavior. These are the key attributes associated with SO that raise it above simple adaptability, as inferred from the definitions discussed above.

1.1.2. Characteristics of Self-Organization

Research on previous wireless network application of intelligent dimensioning, planning, operating and supervised can be summarized/classified by the following:

1.1.2.1. Scalability

Scalability is one of the most important restrictions when SO is implemented for engineering problems. Especially, in all of the wireless network challenges and tasks. The scale size of the system should be limited. So, before running any kind of Self Organization toward any kind of general problems it should remain in local and simple behavior, briefly the system remains operational under SO if a reasonable number of entities leave or enter the system. The main factors that should be supervised are Minimal Complexity and Local Cooperation. It is clear that the algorithms should be conservative in terms of time, space and any other resources that have been used as an input to the algorithm from the system which means less complexity. The second consideration is algorithms should not require global cooperation or signaling, rather local coordination should be relied upon where possible[108] [109]. This moves us toward reducing any overheads because if cooperation among all nodes is required for implementation of an algorithm its overheads will increase as the number of nodes increases in the system. Preventing its scalability. As the updating process looking to local minimum increase to match the prognoses [106] [107].

In sum. All this as in the theory of SO, Scalability can be perfected with minimal complexity and, local control. Which is highly recommended for satisfying the need for Stability and Agility.

1.1.2.2. Stability

This factor is always the main parameter in any Engineering Systems, and any algorithm added to the system should consider this factor. As the Self Organizing (SO) algorithm transmits from state to another within a certain time internationally, the transient time should be finite and feasible. It is not allowed to the algorithm to be oscillating for long time without any converging to stable state. Bounded time really needed for oscillating to maintain the stability. Stability is an important topic for researchers of Self Organizing algorithms, and the main restriction that want to be granted is **Robustness.** Robustness is the safety belt of stability, robustness means that when the system is in a certain state and it is facing a such even cause instability or leads to instability the system needs to be able to return back to the previous state to be stable, and this should be done with a certain "finite" time, and the system should not do a such a flip flop between states during finite time. Stability means the system needs to be elastic, self-healing and not centralized control.

1.1.2.3. Agility

The agility factor is one of the core factors in Self Organizing algorithm. Because SO should applies the adaptation to the system each time it has been called, adaptation should include flexibility and fast response. The best definition for agility in Self Organizing is “supple or acutely responsive’ when the algorithm is in its adaptation to the changes in its operational environment. So, in order to be self-organized, algorithms should not only have the capability to adapt and cope with its changing environment (stability), it should also not be lazy in its adaptation (agility). Meanwhile the system should not be effected by any minor events (neglected updates) it faces during the transient period between one state and another as it has been described in the previous factor. This means there should always be a threshold value for the SO algorithm to decide if it will neglect this even or adapt it. The feedback that the system has to translate as an action by the Self Organizing algorithm plays the main role in all action, its timing is important to it agility and its delay as well [100] [105].

Therefore, scalability, stability and agility are the main factors that need to be monitored while Self Organization algorithms are running toward converging. Self-Organizing (SO) algorithms could be presented in different networks in wireless communication systems, these representations are Adaptive Networks, Autonomous Networks and Cognitive Networks. Based on the literature review that has been done in previous work with wireless communication, the following is a discussion of the three types of networks:

1-Adaptive Networks: This kind of technique depend mainly on the feedback that the system is providing to the control section, so the control section would check the feedback readings and configure it with the closest class, then the order will result in indirect response from the control section to the system [85] [86] [102] [103].

2-Autonomous Networks: It is completely the same as the Adaptive Networks with no human interaction or any other external interaction with the algorithm. It is clearly a Self Monitored system.

3-Cognitive Networks: as [16] explains these types of networks, it is clear this is the highest stander level of the networks that exist now. It is the same as the Autonomous Networks with more facility reaching the environment, reading from it directly, and then applying the adaptation process. Therefore, this network type is capable of planning, observing and executing by itself. The key part of cognitive networks is their interaction with the operating environment and their ability to learn from the process.

1.2. Summary of Work

After comprehensive review of LTE communication systems spectrum and its structure, we describe our main challenge as Resource Blocks allocation in the Resource Elements grid. The grid has been structured based on the standards released by FCC and 3GPP. The main new feature in LTE communication systems is the ability to provide feedback from the end user (User equipment) to the provider (E node B); this feedback includes indications about the channel quality and status between an end user and base-station (E node B) during the last transmission time. Such feedback features are opening the scope toward enabling smart networks that adapt the Resource Elements grid map to improve performance at each transmission period. A specific feedback feature, known in the communication industry Channel Quality Indicators (CQI), can be exploited carefully with some considerations. One needs to consider a certain level of "fairness" while seeking to accelerate the downlink throughput. Because if one keeps sending packets to only UEs that have high quality channel status, other UEs with less quality channels will become neglected for a relatively long time. Thus, it is judicious to infuse throughput performance and some sense of “fairness.” In this process. In this work, we introduce adaptive intelligent techniques that update the Resource Elements grid, taken in considerations the statistical mean channel quality (CQI) of the linked users over intervals above certain threshold values[54] [57] [61].

The main work here is to build smart scheduler at the (E node B) level in the downlink and this needs pre-scheduling and post-scheduling procedures such as mapping the users in the grid. These procedures have been developed in details in the next chapters[50] [51] [52] [53].

1.2.1. Developing Modified Self Organizing Map technique:

The Modified Self Organizing Map technique adds the non-linearity toward fast adaptation. This is one of the main contributions in this work. We are using a modified form of updating the weights. In this novel algorithm, the updated weights are energy based and the updated function includes non-linearity. This helps our case, as we want to do mapping with clustering in one direction.

$$\Delta W_K(n) = \eta(n) h_{ik}(n) (X(n) - W_k)^{3} \qquad \text{for } K \in N(i) \qquad (1.1)$$

This modified updating is smoothing the values of the weights at each transmit time, and the benefit is accelerating the convergence of the weights, which are visible for our case here. This has been covered in chapter 3 in details and proofs.

1.2.2. Implementing Modified SOM to Schedule Resource Blocks of LTE Communication Systems

The way we are applying the Self Organizing Map is the weights are carrying the Channel Quality Indicators updates of the channels. This means number of weights are equal to the number of users. The weights are updated at every transmitting period. Therefore, we are looking to the weights to be converged very fast and passing the warming era soon. At each transmitting period we use equation (1.1) to carry the update of the channel performance. This is happening all time long once at each transmitting period and the mapping decision are happening at each transmitting period as well. This has been covered in details with performance evaluations at Chapter3.

1.2.3. Applying Recurrent Neural Network Toward Providing Future Predictions

The base Recurrent Neural Network (bRNN) that has been introduced in [38] exhibits stable behavior and uses training capability that enable prediction. We implemented as system that employs bRNN that enables the prediction of the next users' channel quality after initial training periods. Such prediction enables the system to schedule the Resource Blocks to flexibly optimize performance. More details and evaluation of the modification are provided in Chapter 4.

1.2.4. Implementing bRNN to Schedule Resource Blocks of LTE Communication System

We build our own base Recurrent Neural Network that introduced at [38], then we modified it by adding the prediction calculation state. This prediction provides us with output at each iteration as well as error management and performance evaluation. All this are happening with updating our code with the regular way that has been introduced at [38]. Here we are applying our input training data as the vector of the Channel Quality Indicators, we are applying this input data at each transmitting period and we update the weights matrices as well as providing future perdition of the next transmitting time which considered as feed for mapping the Resource Element grid.

The performance evaluation that has been explained in chapter 5 shows how high throughput of the e node B downlink as well as how smooth the individual users throughput are.

Chapter 2. Implementations of Self-Organization in Cellular Networks

In this chapter, we discuss my survey from the previous publications on the Self Organizing Algorithm in Wireless network and communication systems. The previous research work has been classified, some classes are already highlighted in Chapter 1. Specific classifications are introduced here in Chapter2.

We categorize the previous research on Self Organization in three parts corresponding to the phases: Self Configuration, Self-Optimization and Self-Healing [98] [99].

Each of these Phases has two schemes of Self Organization (SO) on them. We used a Framework to characterize the use of Self Organizing (SO) in this report as a general barometer to assess the degree of SO in the proposed solutions where applicable.

2.1. Self-Organization in Wireless Communication

Based on 3GPP [17] and NGMN [18] We reached to a brief list of cases where Self Organization algorithms applied to:

1- Inter-Cell Interference coordination

2- Interference reduction

3- Energy saving

4- Automated configuration of physical cell identity

5- Coverage and capacity optimization

6- Mobility robustness optimization

7- Mobility load balancing optimization

8- Random access channel (RACH) optimization

9- Automatic neighbor relation function

We categorize the use of Self Organizing (SO) in these nine classes. However, some previous publications tried to classify any kind of work under one of the four main system objectives i.e. coverage expansion, capacity optimization, QoS optimization and Energy efficiency [19] [96] [97].

lternatively, Self-Organization use could be classified either to be an online control solution or offline control solution, usually in wireless networking they applied Self Organizing into online solutions, which is more accurate and flexible on adaptation as [23].

In terms of classification, there is an-other point of view to be considered: depending on the challenge that brought Self Organization to the table they classify the SO use, as in previous publications [20], [21] and [24] they divided the SO into three main categories of classification: time case, space case and phase case.

It is clear on time scale based classification the main factor is the operating time of the SO algorithm. From the literature, we observed the adaptive modulation and coding scale are in the same class, and the power control load balance is in other class. Therefore, Phase Based Classification has three main phases deployment, redeployment and maintenance. There are some official classifications for these phase classes on Artificial Neural Network publications; they are **self configuration, self-optimization and self-healing.**

Each phase of these main phases can be highlighted into different paths as figure (1) shows,

Figure 1 Classification of SO use in Wireless Communication.

2.1.1. Self-Configuration

Configuration became a mandatory operation in wireless communication system. It is needed for eNode Bs (eNBs), femto cell, small sell and relays. It is done through deployment, extension, and upgrade of any terminal. Configuration is important in the test and drops on the services. As LTE and LTE-A are on massive scale in terms of terminals. Therefore, Self-Configuration has to be attached with these networks for comfortability and accuracy.

From past productions of models we have examined, the Self Configuration principle intention is: the point at which a disappointment happens into a specific terminal this terminal ought to have the capacity to come back to running mode with no human inclusion. This procedure and the executions of Self-Configuration can be abridged into these following features:

2.1.1.1. IP Address Self-Configuration

Self-Configuration has been implemented in wireless technology, and it has been implemented on computer networks in IP-addresses like into Dynamic Lost Configuration protocol or in Bootstrap protocol. There are several flow charts for this process, as in [25] there is great use for Self-Configuration in e Node B.

2.1.1.2. Neighbor Cell List Self-Configuration

One of the most promising use for Self-Configuration in LTE and LTE-A is to be used in making a list of ID for the surrounded cells with the e-Node B, where the cell ID list should be implemented and updated frequently[94] [95]. This is done by generating a neighbor cell list and updating it using a centralized as well as decentralized approaches. The criteria for the selection of neighbors or the initial generation of the neighbor cell list can be based on the geographical coordinates of the cell sites.

2.1.1.3. Radio Access Parameter Self-Configuration

This is one of the promising field for Self-Organizing SO in wireless communication systems, because its effect will be observable and will affect the network in terms of operating and resources values. Based in previous publications we have scanned; we can summarize it into:

2.1.1.3.1. Frequency Allocation Self-Configuration

It deals with the MAC layer frequency channel for Peco, Macro, Micro, and Femtocell [25]. From another viewpoint, there are some algorithms that start to be presented, which reuse the resources (Bandwidth). Like in [26]. This kind of work does not have an expandable future.

2.1.1.3.2. Propagation parameter configuration

I’s popular topic now, because with initialized parameters, networks need offline updates so the cell will not affect the neighbors or the neighbors will not affect the cell. Dynamic Radio Configuration Function (DRCF).

2.1.1.3.3. Self-Confirmation Management

This work depends on Resource Information Base RIB and Policy Information Base PIB based in data analysis.

2.1.1.4. Self-Organization promises for Operators Policies

The Operators policy are the rules that have been agreed on by governmental organizations like FCC or 3GPP in their releases. These rules are clear and they could be classified into coverage extension, capacity optimization, energy efficiency or fairness among users. The rules could be rules affect all of these classes at one release [92] [93]. There are some proposals in the publication for some regulations to configure management for the operators.

These configuration management mechanisms could rely on data like resource information base or Policy information based.

2.1.2. Self-Optimization:

As in any running systems, optimization is a huge goal to implement by Artificial Neural Network algorithms. There are many publications releases toward using Artificial Neural Network into LTE networks and LTE-A and there are promises to use Self Organization (SO) specifically. Some publications introduced Self Optimization for Load Balancing, Self-Optimization for Capacity and coverage and Self Optimization for Interference Control. The Self Optimization for Interference Control is promising solution to LTE and LTE-A networks challenges, like for the main challenge for the capacity in these networks are Inter Cell Inter Carrier (ICIC) and it is making a huge effect in the coverage as well.

2.1.2.1. Self-Optimization for interference management: (long term)

In such types of networks, frequency reuse is small and most likely one, this really effects the QoS through the interference that is happening[91]. This tighter frequency reuse needs a lot of co-channel optimization to cleave the trade off and this really needs to stay in the long term, here are some examples of this:

2.1.2.1.1. Self Optimization through ICIC

A- Self Optimization via Integer Frequency Reuse

B- Self Optimization via Fractional Frequency Reuse

2.1.2.1.2. Self-Optimization through Dynamic ICIC

2.1.2.1.2.1. Self-Optimization of Capacity and Coverage via Relaying

Self-Organization using Self Optimization has been summarized into figure (2) as the previous publication stated

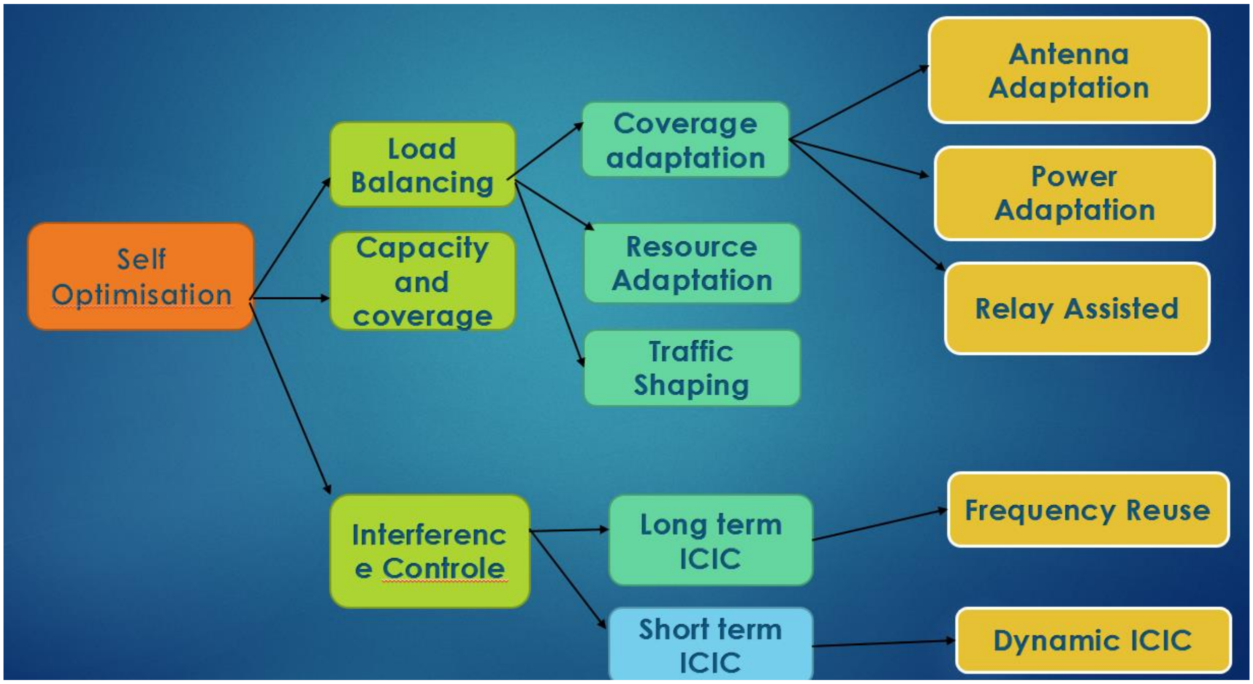

Figure 2 Main uses on SO for Self-Optimization.

2.1.2.2. Self-Optimization for Load Balancing:

Promptly after the coming of marketed cell correspondence frameworks, the arrival of common spatio-transiently differ client circulations due to the requirement for the heap balance components[87] [89] [90]. From that point forward, numerous productions seemed to receive the Self Organization (SO). In any case, this past work with remote correspondence is excessively particular, making it impossible to these distinctive sorts of Networks and there is no such calculation that has been actualized to LTE or LTE-A systems. This is the reason this work we are doing here, this is the reason our work is huge, putting forth a concentrated effort Organizing (SO) to Self-Optimization the heap balance; it is possible that it will be in the Physical Layer or into MAC Layer. Before we experience our work. Quickly, a thought of past examinations is incorporated here before a dialog of our investigation:

2.1.2.2.1. Resource Adaptation based for Load Balance:

This Research is important for most types of wireless networks. Excluding OFDMA such LTE and LTE-A. Usually such networks that use one frequency for all cells and because of the Inter Cell Inter Carrier ICIC will be high in such scenario, especially if the cell borrows some channels from the neighboring cell. There is a massive work in the WCDMA network on building algorithms of virtual channels. Therefore, if the cell was busy and the neighboring cell was not in the full load, the neighboring cell could borrow some channels and use them virtually. Again, this is not currently visible.

2.1.2.2.2. Traffic Shaping based Load Balancing:

This theme is not that appealing so far to LTE and LTE-Advance, Ordinarily Movement Forming is extraordinary with tolerating another association or in the hand-over. In LTE and LTE-An as they are utilizing one bearer recurrence there are no soft Hand-Over or considerably Gentler Hand-Over, if there are hand over happening it is in every case Hard Hand-Over. In systems like WCDMA, this is extremely encouraging in light of the fact that when another association is set up the system will need to be keen with snaring it inside the correct cell from the earliest starting point. This cell ought to be free and give a decent inclusion to the area, a similar thing with Delicate Hand Over and Milder Hand Over. This procedure should be done scientifically to give great Load Equalization.

2.1.2.2.3. Coverage Adaptation based Load Balancing

This type of load balance is done by a certain mechanism of change that effects coverage:

2.1.2.2.3.1. Load Balancing via Antenna Adaptation:

Most of the publications in this topic are talking about how the tilting of the antenna can be changed for favor of improving the coverage and no user will be terminated because of coverage. In Networks like WCDMA, this is not a big deal as there are always soft-hand over with subscriber. In other wireless communication systems this is still big issue, there are many creative papers talking about how they could oscillate the antennas to improve the coverage or cover certain spots.

2.1.2.2.3.2. Load Balance through Power Adaptation (PA)

Transmission power can act naturally self organized. For the most part here we don't discuss Agility or Scalability. A large portion of the discussion is tied in with controlling the Pilot Signal regarding its quality. This sort of control should be possible in the e-Node B itself or in more elevated amount stages like MS terminal. The parameters that will be controlled are totally not the same as the Soft Hand over parameters; here we change the inclusion quality to show signs of improvement Load Balance execution. These sorts of plans generally are done Online despite the fact that there are a few distributions like [27] talking about Self Organizing the Power off-line.

2.1.2.2.3.3. Load Balance through Hybrid Approaches

From the title, it is clear it is a mix of Soft Hand-Over and Power control, some publications as in [28] start to use both techniques at the same time to improve Load Balance on Traffic Shaping. Because, of central control on this lack of scalability appears, the use of traffic estimation maps that have been done by operator systems it will be dynamic. It is a more efficient offline design methodology, more useful during the deployment phase, than an online LB mechanism implementable in the operational phase. There are similar shy work with WCDMA networks.

2.1.2.2.3.4. Relay Assisted Load Balance

From some studies like [29] there is a possibility of controlling the Load Balance through the relays by these tools:

There is intensive research on the previous three points into WCDMA networks as well as the Ad-Hoc networks in terms of Load Balance and Load Sharing. Such a work is usually done by a central control unit which is still required to receive, process, and feedback the dynamically changing system wide utility to and from all UE and relay nodes in the network. This may have an adverse effect on the agility of the solution in a practical system because of the delays incurring from large amounts of data processing and its relaying to and from a central unit.

2.1.3. Self-Healing

Remote correspondence frameworks like some other designing frameworks can possibly bomb every once in a while. This happens on account of outside impacts like catastrophic events or mishaps or inward deceptive of the framework. As of now, if there are any sort of disappointment answered to the administrator, RF-Engineers and experts will go to the area of disappointment and run the investigating at that point run their technique to illuminate the issue and restore the framework to the standard dynamic mode. It is clear this disappointment could happen to some degree frequently and this requires some investment and a ton of endeavors to restore the framework to customary mode. The presence of the Artificial Intelligent Self-Healing model turns into a promising subject in this title. Accordingly, there are many promising stream graphs and introductions of the Self-Healing model beginning to show up in meetings and productions. 3GPP in its discharge discussed Self-Healing and attempted to guarantee sorting out the procedures that will be utilized at that point. The general methodology towards Self-Healing is recommended, that comprises of essential components of observing, determination and pay. Learning and adjustment is likewise certainly part of this methodology as off base determination dependent on wrong relationship of alerts can be logged for a more savvy conclusion in future. The primary periods of Self-Healing are: Monitoring, Diagnosis and Compensation.

One of the general Framework of Self-Healing which is the regular situation can be condensed here:

In the ordinary dynamic mode, the framework is checking the system for any peculiarity or if any predefined conditions for Self-Healing conditions are fulfilled. Along these lines, when such conditions are met, information are broke down utilizing the Self Organizing calculation or by any framework master to determine the sort of deficiencies (with a specific likelihood of precision) and afterward the neighboring cell for the fizzled cell ought to be enlightening toward covering loss of this phone (redress), Hopefully this remuneration will be in full for the flawed hub. The neighboring hubs likewise occasionally tune in to signals from the broken hub by means of the X2 interface to set up if the hub has been reestablished. At the point when the neighboring hubs can come back to their pre-remuneration mode then as not to debase by and large framework execution by impedance this must be precise on timing. A critical element to be watched is the circle that persistently screens the defective cell to decide whether it has been reestablished to typical activity.

Despite the fact that there are many promising works in this field, it will be moderate on the grounds that such work in Self-Healing should be finished with existing frameworks. This work should be done under supervision of the Operators which are now running with gigantic measure of directions by various Organizations. The primary Detection and Compensation plans found in productions are:

2.1.3.1. Cell Outage Detection Scheme

The cell is considered to have an outage when its performance (Coverage or Capacity) is below a threshold values, which is most likely specified in the standards of the technology. Usually there are types of Outages in public references.

2.1.3.2. Cell Outage Compensation Scheme:

It is always dependent on the faults that has been detected. Therefore, before any action of compensation, the fault has to be clarified. This clarification could be done automatically or manually because it could need a visit to the E-node B location. [29] presents a cell outage management description for LTE systems. Both the detection and the compensation schemes highlighting the role present a cell outage management description for LTE systems.

Chapter 3. LTE Resource blocks structure Types

This work is not only having potential toward an upgrade for the 4G+ type of wireless communication systems. This work is a development to the innovative technology because it is applicable to the 5G wireless communication systems. Radio Access Network RAN sharing for 5G wireless communication system can be implemented by adding advanced control features to the current 3GPP LTE which will be the dynamic scheduler. LTE uses Orthogonal Frequency Division Multiplexing (OFDM) for the downlink and Single Carrier Frequency Division Multiple Access (SC-FDMA) in the uplink [44] [60] [62] [63]. The Physical Resource Block (PRB) is the smallest element assigned by the base station scheduler [84]. Transmission Time Interval (TTI) is the duration of a transmission on the radio link, which is exactly the same structure we are talking about here in our work. A scheduler can determine to which user the shared resources (time and frequencies) for each TTI should be allocated. The RAN sharing problem is related to the design and implementation of policies that are able to effectively schedule Resource Blocks effectively between different MVNOs with respect to specific differentiation objectives and with isolation guarantees.

As currently, the only available Matlab simulation toolbox is for LTE-A 4G+ communication. We applied our algorithm to this type of simulation with capability of applying it to 5G simulation in the future

3.1. Scheduling and novel scheduling algorithm:

As LTE and LTE-Advance are the latest versions of mobile communication networks proposed to the customers to use through several organizations like 3GPP and FDD. They are using the latest technology in the field, especially Frequency Division Multiplexing Access (FDMA) for downlink, Orthogonal Frequency Division Multiplexing Access (OFDMA) and Single Carrier Frequency Division Multiplexing Access (SC-FDMA) for up-link with using some other technology like MIMO as well [48] [49]. Our work will be in the downlink of the network as the bottleneck challenge is the capacity (throughout and latency) in down link from the Evolved Base Station (E Node Base):

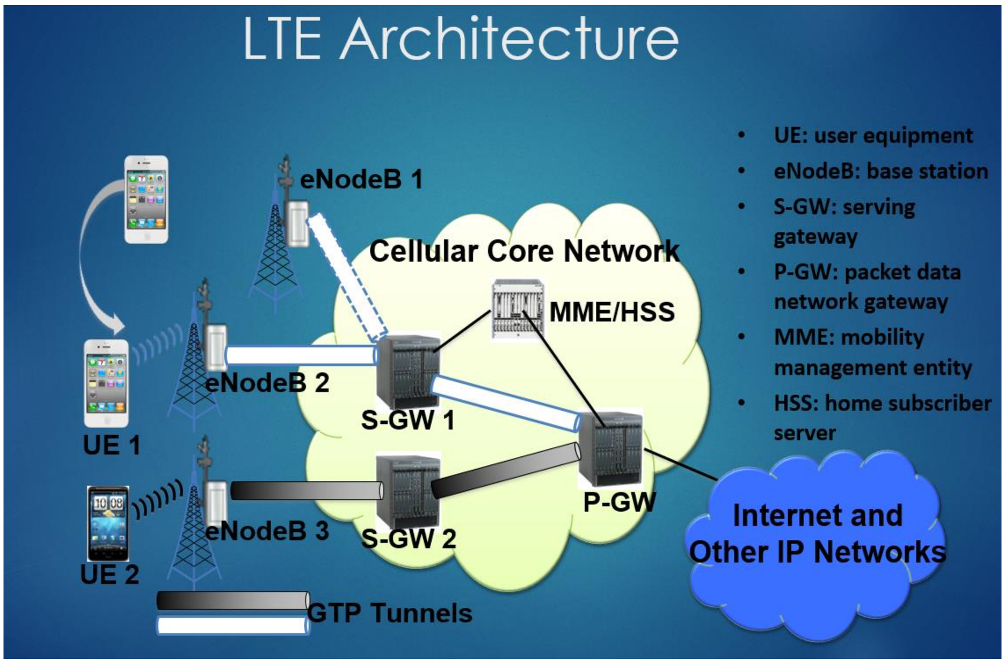

Figure 3 LTE Architecture.

There are two frame structures in LTE slandered: Type 1 uses Frequency Division Duplexing (uplink and downlink separated by frequency)[45] [70] [74], and TDD uses Time Division Duplexing (uplink and downlink separated in time). Both of these frames are used at LTE networks at the same time, in order to adequately explain OFDMA within the context of the LTE, we also must study the physical layer generic frame structure of LTE networks [55] [56] [59] [64].

Therefore, just currently 3GPP released the main structure of LTE- A and its specifications. It is clear OFDMA provide a lot to the scheme, for example: time and frequency diversity, good resistance to inter-symbol interference, better deployment flexibility. Besides, OFDMA allows assigning subsets of OFDM subcarriers to different mobiles for achieving multiple access.

3.2. OFDMA and the LTE generic frame structure

Even though OFDMA involvement in adding complexity into Resource Scheduling. But, it is the best choice of multiplexing scheme for 3 GPP LTE down link. OFDMA is vastly superior to packet-oriented approaches in terms of efficiency and latency[65] [67] [68].

The best way to define the structure of the downlink: The users are allocated a specific number of subcarriers for a predetermined amount of time. These are called physical Resource Blocks (RB) in general in the LTE specifications [80] [81] [82] [83]. RBs thus have both a time and frequency coordination. Allocation of RB is handled by scheduling function or operator in the (E node Base). In reality, there are smaller units than the Resource Block called Resource Element (RE) and it is the smallest unit in the frequency time structure. RE is clear in figure (4) and it is not important in scheduling as each user in scheduling process will be assigned a number of Resource Blocks (RB) as shown in figure (6) how grouping a certain number of Resource Elements become one Resource Block[69] [72] [75] [77] [78].

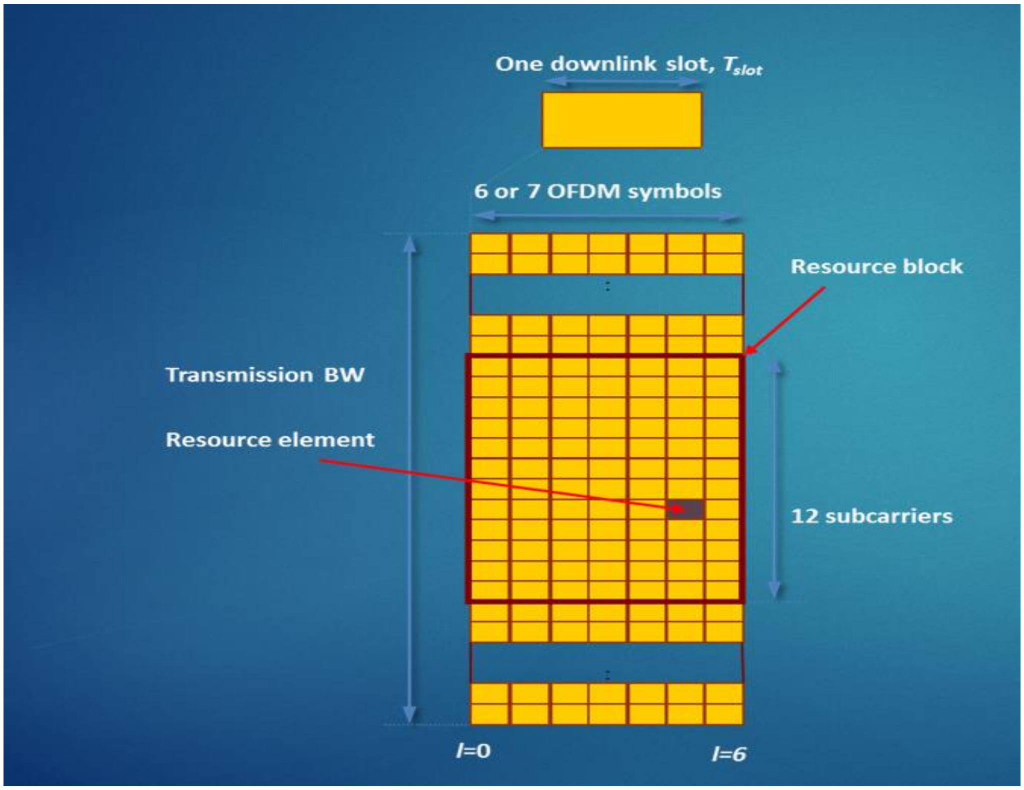

Figure 4 Resource Grid

LTE frames are 10 m Sec in duration. They are divided into 10 sub frames, each sub frame being 1.0 m Sec long. Each sub frame is further divided into two slots, each of 0.5 m Sec duration. From the other side, in the same representation, each slot consists of either 6 or 7 ODFM symbols, depending on whether the normal or extended cyclic prefix is employed as shown in figure (5) the 2-dimension Time and Frequency grid.

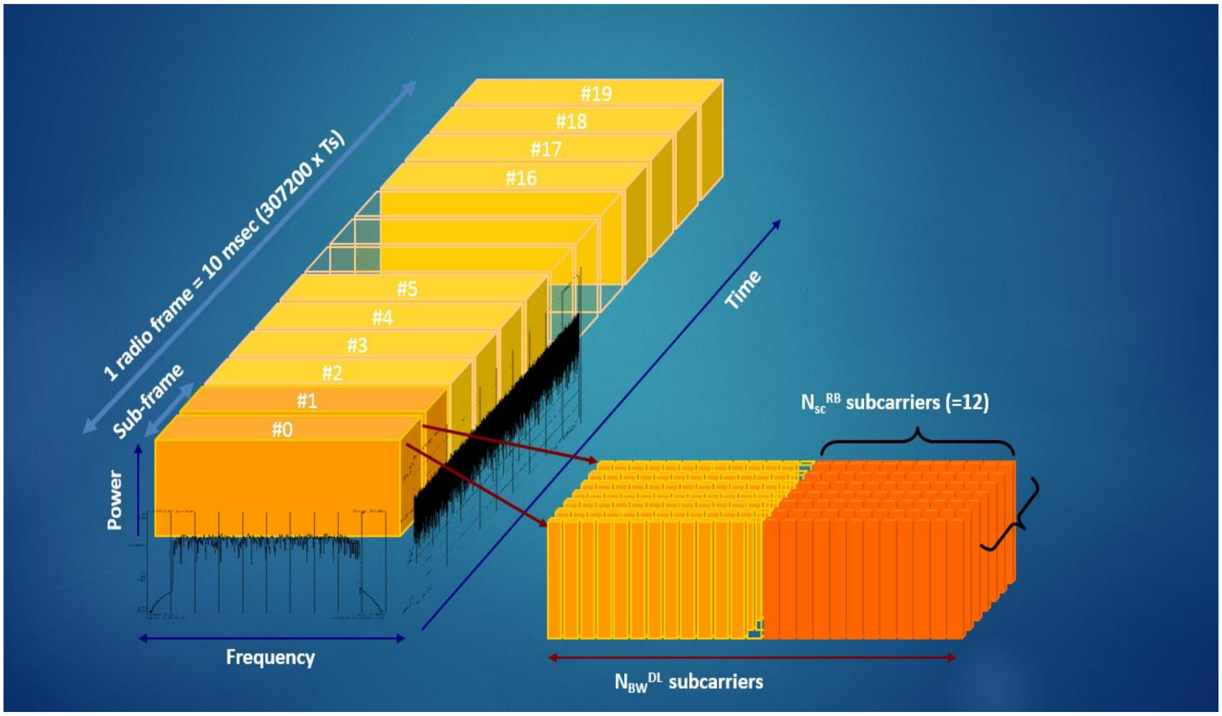

Figure 5 2-D Time frequency grid

The transmitted downlink signal consists of a portion of the bandwidth (N_{BW}) at the same time from an other side of the coordination of a subcarriers for a duration of N_{Symb} OFDM symbols. It can be represented by a Resource Grid as shown in Figure (6). In figure (6) each box within the grid represents a single subcarrier for one symbol period and is referred to as a Resource Element as the dashed boxes are the Resource Block RB the main unit we are dealing with in scheduling[79].

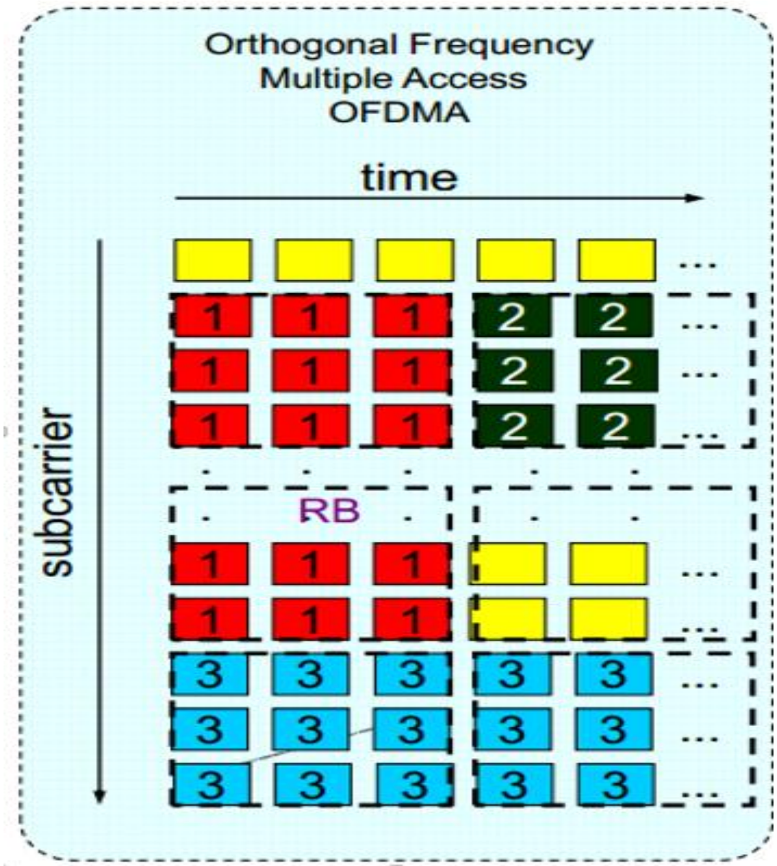

Figure 6 Orthogonal Frequency Multiple Access OFDMA.

In general, LTE does not employ a PHY introduction to facilitate carrier-offset estimate, channel estimation, timing synchronization, etc. Instead, special reference signals are embedded in the Resource Blocks RBs as shown in Figure 7. Reference signals are transmitted during the first and fifth OFDM symbols of each slot when the short Cycle Prefix CP is used and during the first and fourth OFDM symbols when the long Cycle Prefix (CP) is used.

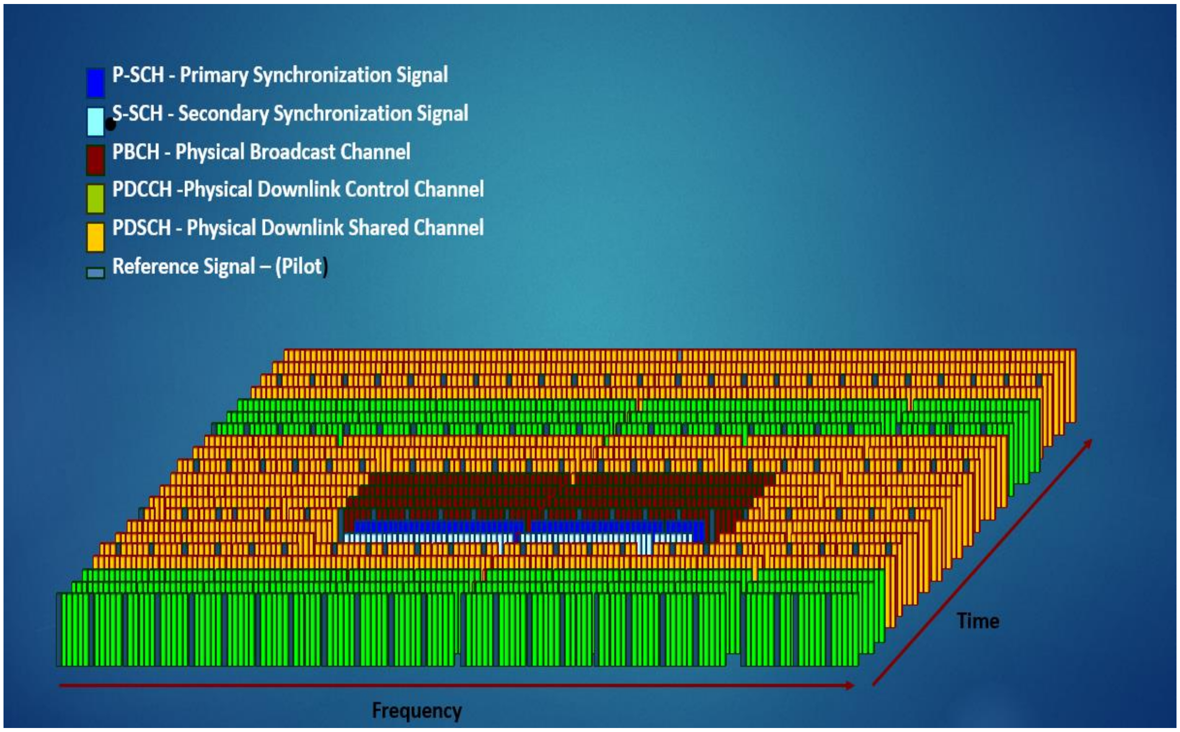

Figure 7 2-DL Channel Mapping

That reference symbols are transmitted every sixth subcarrier. Further, reference symbols as the rest of LTE structure are settled in both time and frequency at once. The channel response on subcarriers bearing the reference symbols can be computed directly. Interpolation is used to estimate the channel response on the remaining subcarriers.

3.3. Vienna LTE-A Downlink System-Level Simulator:

Vienna LTE / LTE-A link level simulator [37] is a Matlab toolbox that has been developed at Vienna University of Technology. This simulator has been used toward evaluating several scheduling algorithms in this work. The main goal of this simulator is to enable the analysis of network performances. This toolbox is capable of providing different base stations in the scenario. However, as our work focuses on the scheduling algorithms in the downlink, we are just applying it with one base station. This way the Region of Interest (ROI) is simpler and no more specific information about it is needed.

Briefly, this Matlab tool box has a link measurement model which is responsible for measuring link parameters. With this link measurement, link quality is demonstrated based on the measurements conducted using user's equipment. This measurement will later be sent to the base station in the form of a measurements report. So, the resource allocation will be based on the adaptation algorithm we are introducing in this work. In other words, the brain of the network is the scheduler. Based on the link measurement model, the link performance model predicts the Bit Error Rate BER based on the receiver signal to the interference ratio (SINR) and the transmission parameters.

3.4. Packet scheduling in wireless technology:

Usually Packet scheduling is called Network Scheduling in the literature. The best definition for this scheduling is: An algorithm (rule) program installed on the E node Base in packet switching communication networks. It manages the sequence of network packets in the transmit and receive queues of the network interface. There are some scheduling algorithms already in existence that are used to manage this control rule.

In this work, the simulation ran into these criteria:

Table 1 Environment Criteria.

Parameter	Value
System bandwidth	1.4MHz
Subcarrier spacing	15 kHz
Channel profile	PedB/Rayleigh
Simulation length	10,000 subframes
Number of users	12
User's speed	1 km/h

The most common algorithms that exist in LTE wireless networks are: RR, WRR, and Max_CQI.

3.2.1. Round Robin Scheduler (RR):

Round Robin is one of the most common implemented algorithms in networking technology in terms of scheduling routine; it is employed by process and network schedulers in computing. Round Robin resource allocation is an algorithm applied toward resource sharing between the users or channels. Typically, in the previous network generation, Round Robin time slices are assigned to each process in equal portion and circular order. Therefore, this process has no conditions and as simple as this: there are no priorities or power in the duration. RR is the same procedure as packet switching in the regular networks scheduling.

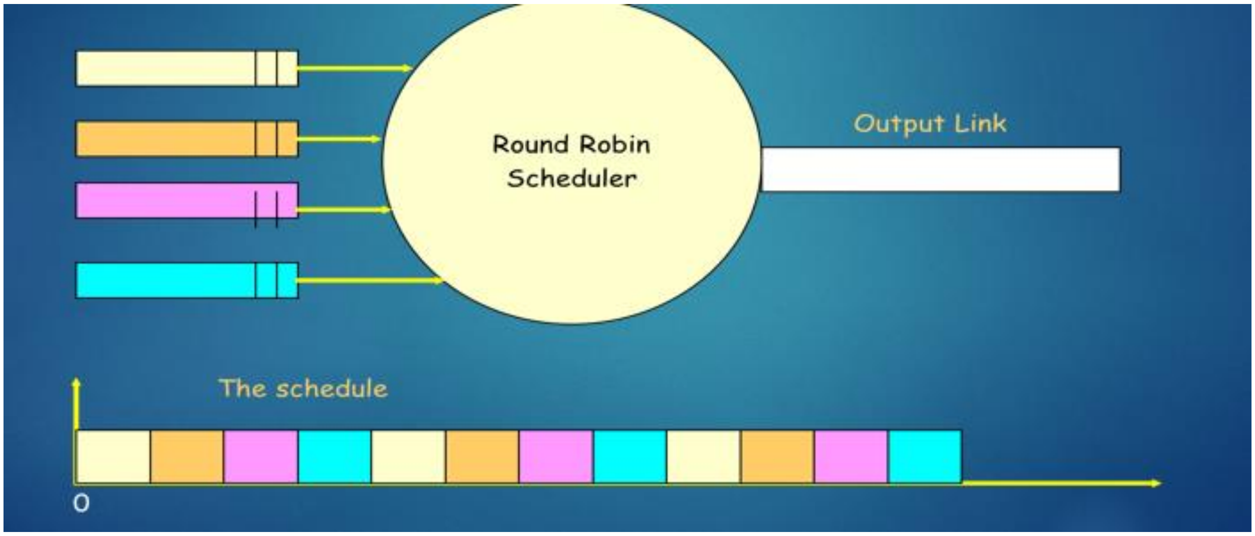

Figure 8 DL Channel Mapping

We applied the Round Robin scheduling technique into the LTE network. This means that all the UEs shared the Bandwidth equally with no conditions.

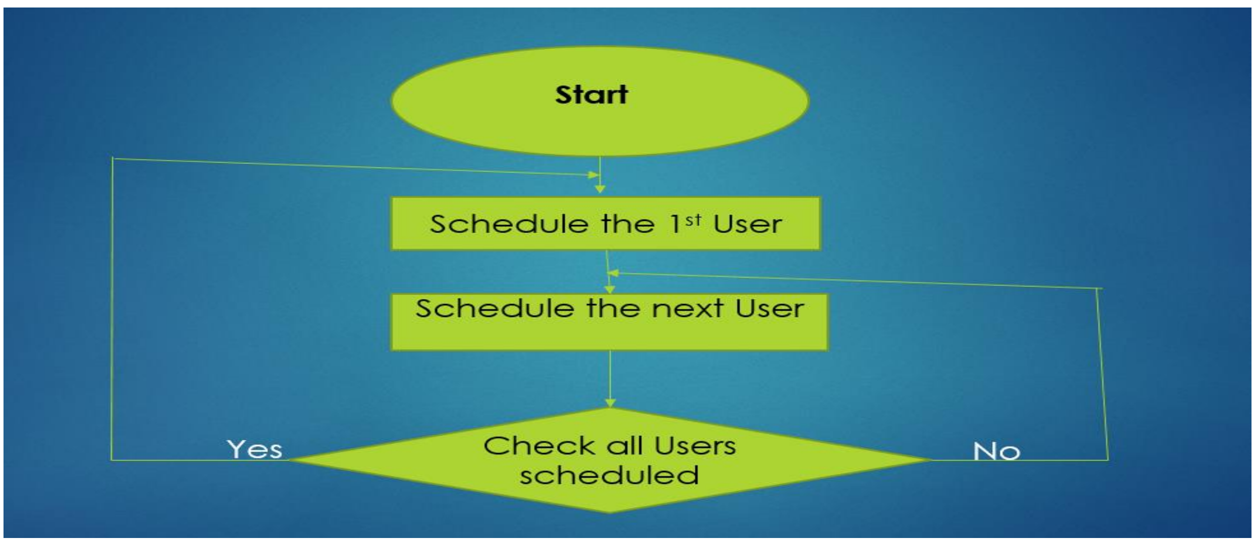

Figure 9 Round Robin Schedule flow chart

By running the simulation, we got the performance shown in next figures starting from figure 10, this performance of the network and the subscribers UEs at certain modeled circumstances in terms of channel type, Channel Quality Indicator, etc. The measurement criteria for the network performance are: Block Error Rate and Throughput in relation to Signal to Noise Ratio SNR for both the E Node Base and individual users. In order to show the development, we provide in the novel technique, we discuss the performance of several individual subscribers UE in the following terms: UE1 Throughput toward spectrum of Signal to Noise Ratio, Block Error Rate for the UE1 toward spectrum of Signal to Noise Ratio. The next plots show the performance for different type of channels by applying Round Robin scheduling technique:

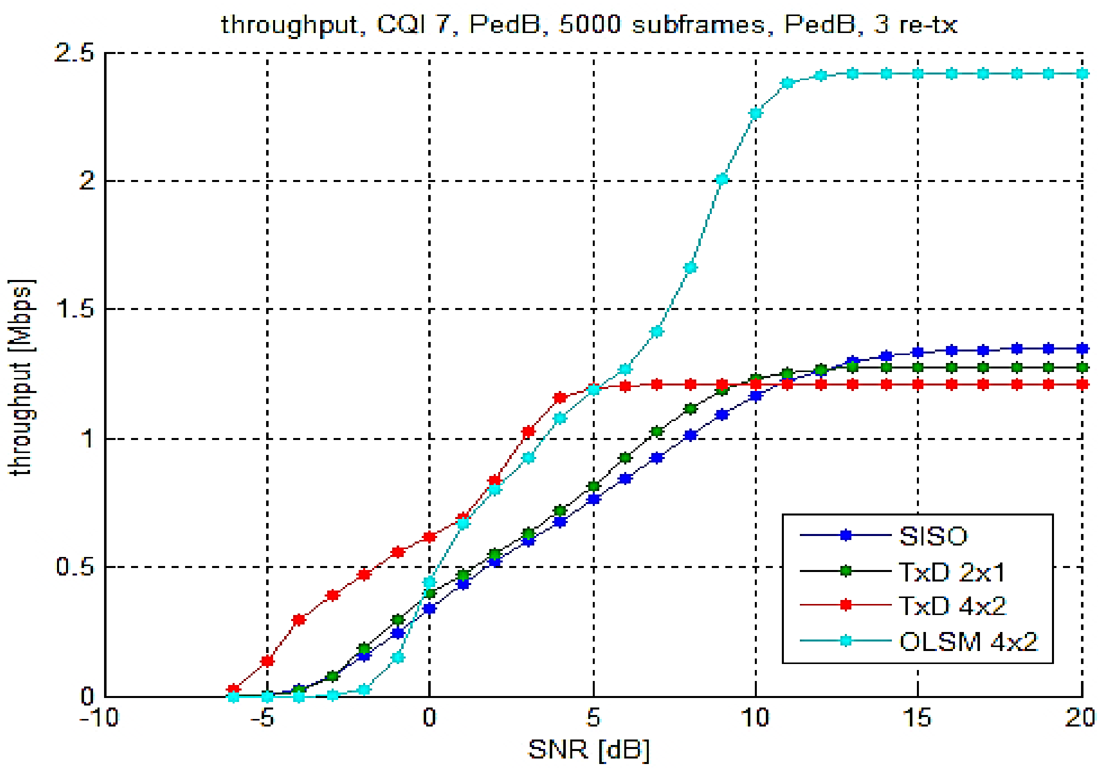

Figure 10 E-node B throughput PedB Channel.

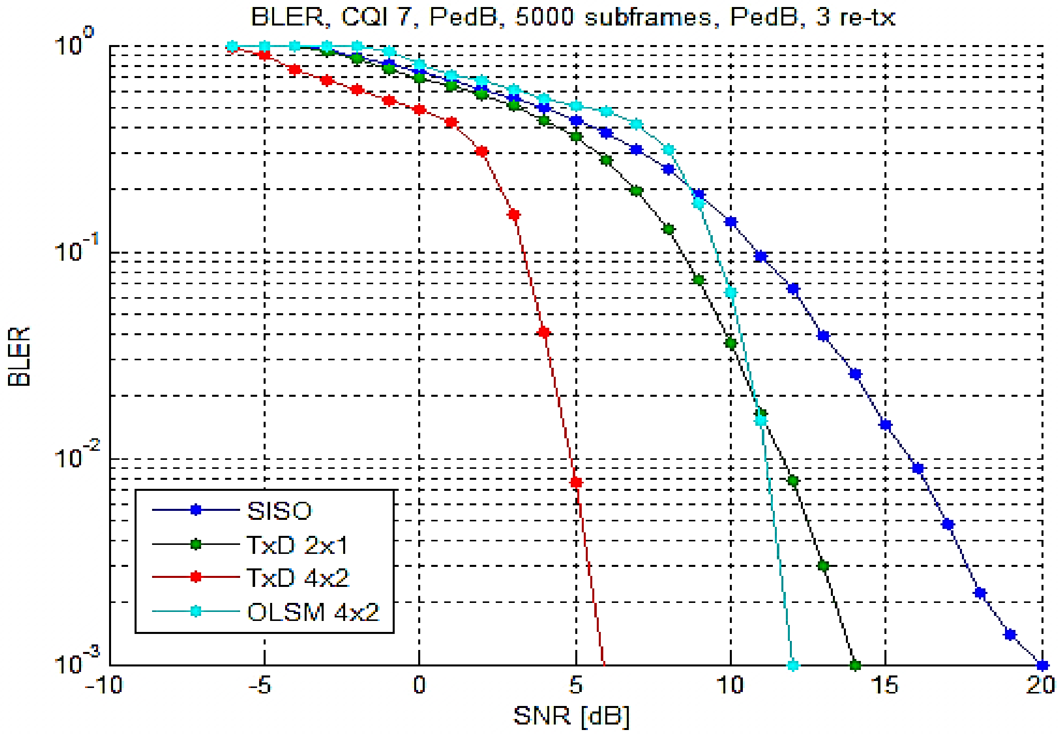

Figure 11 Block Error Rate PedB Channel

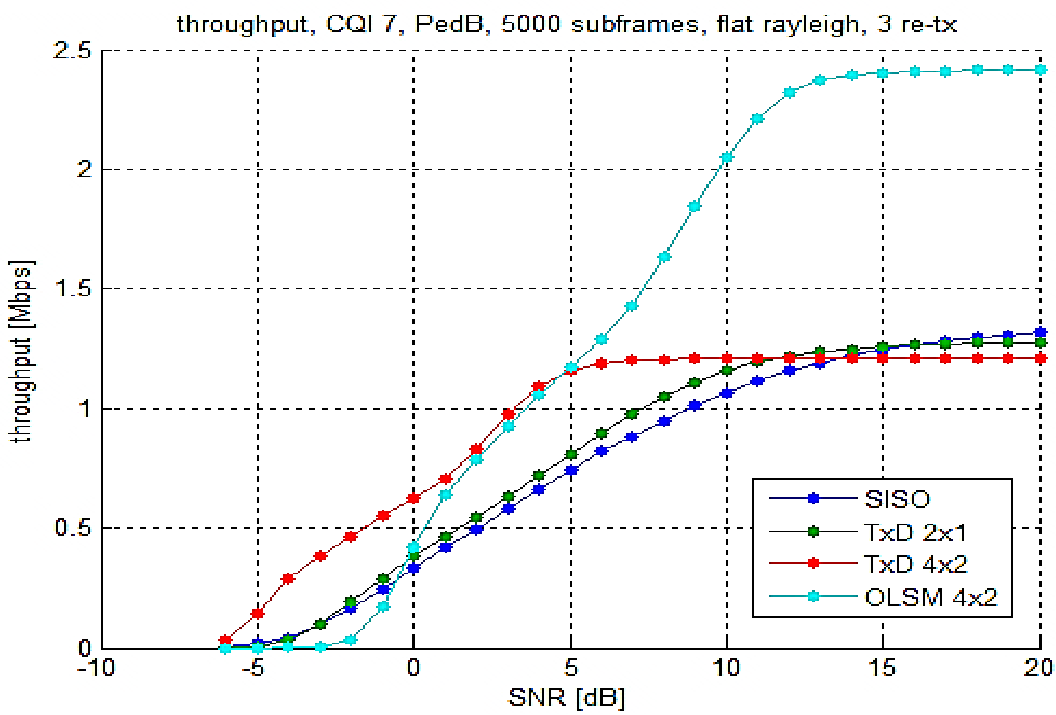

Figure 12 E-node B throughput flat Rayleigh channel

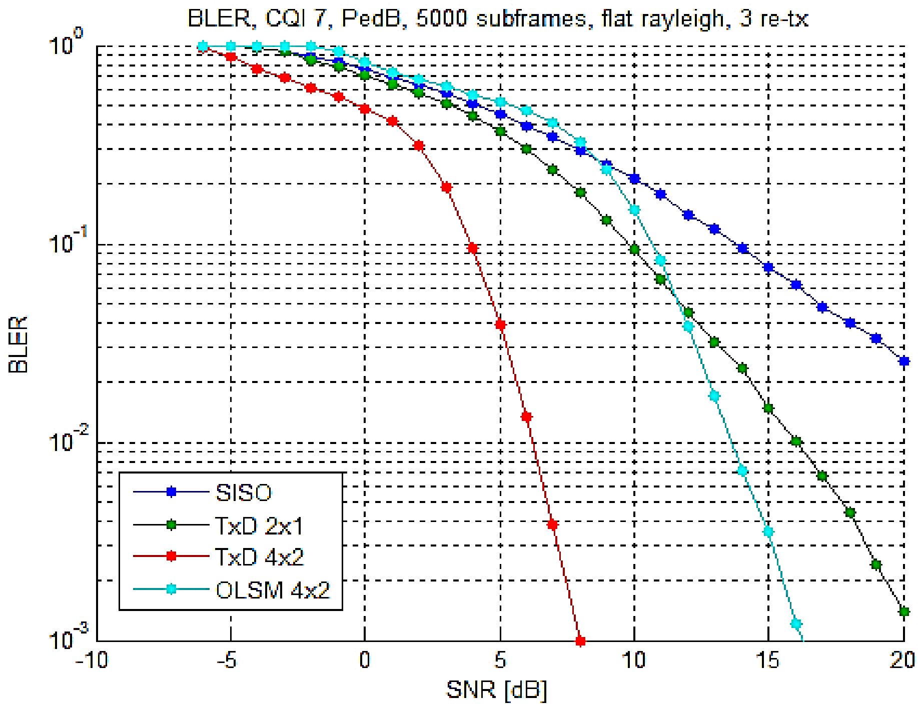

Figure 13 E-node B Block Error Rate Flat Rayleigh channel

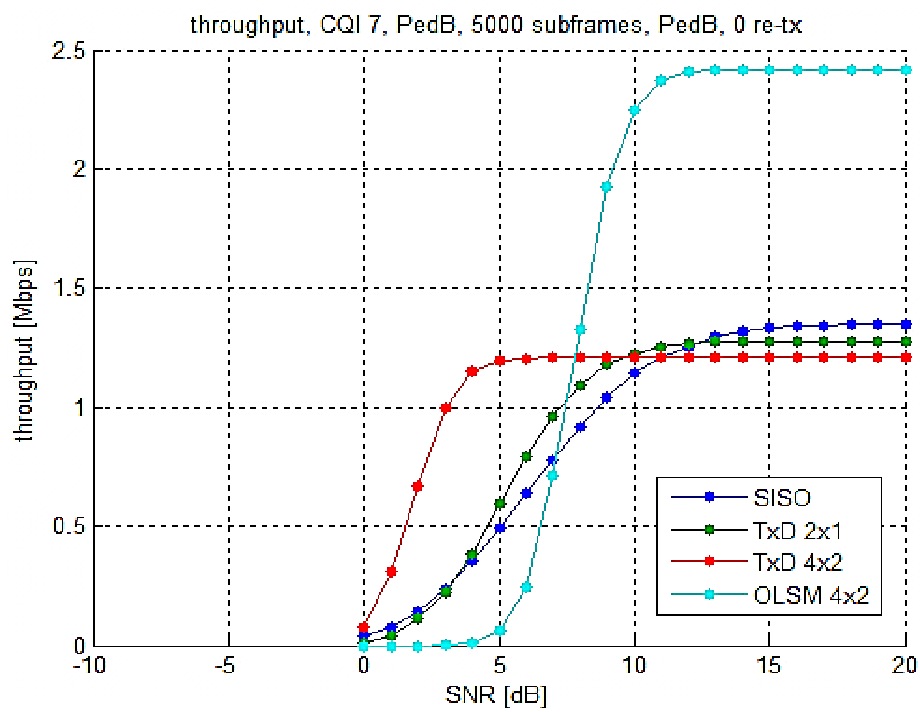

Figure 14 E-node B throughput PedB channel

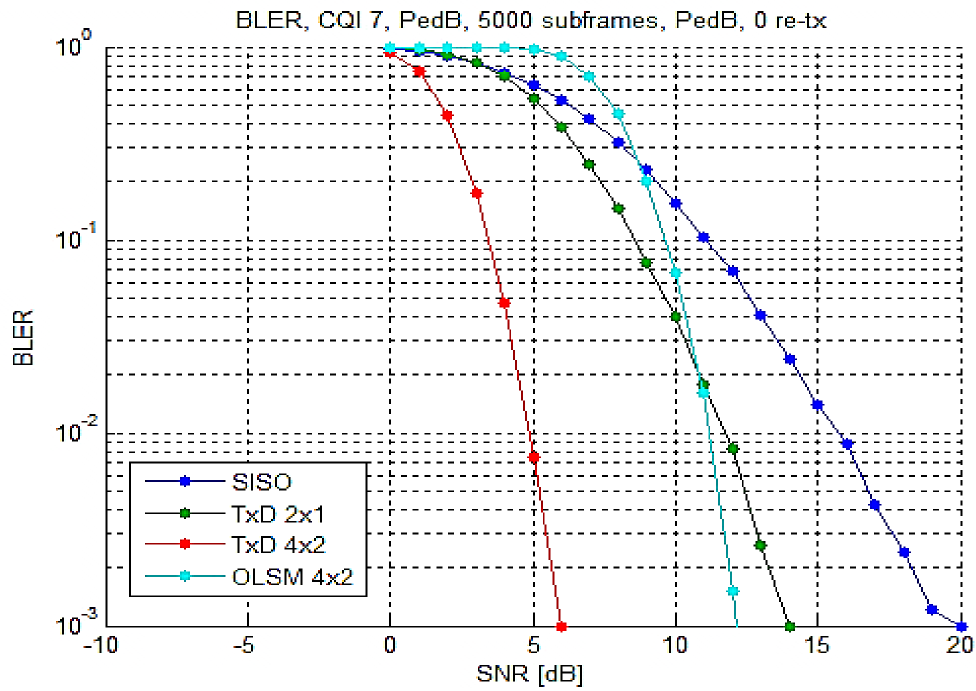

Figure 15 E-node B Block Error Rate flat Rayleigh channel

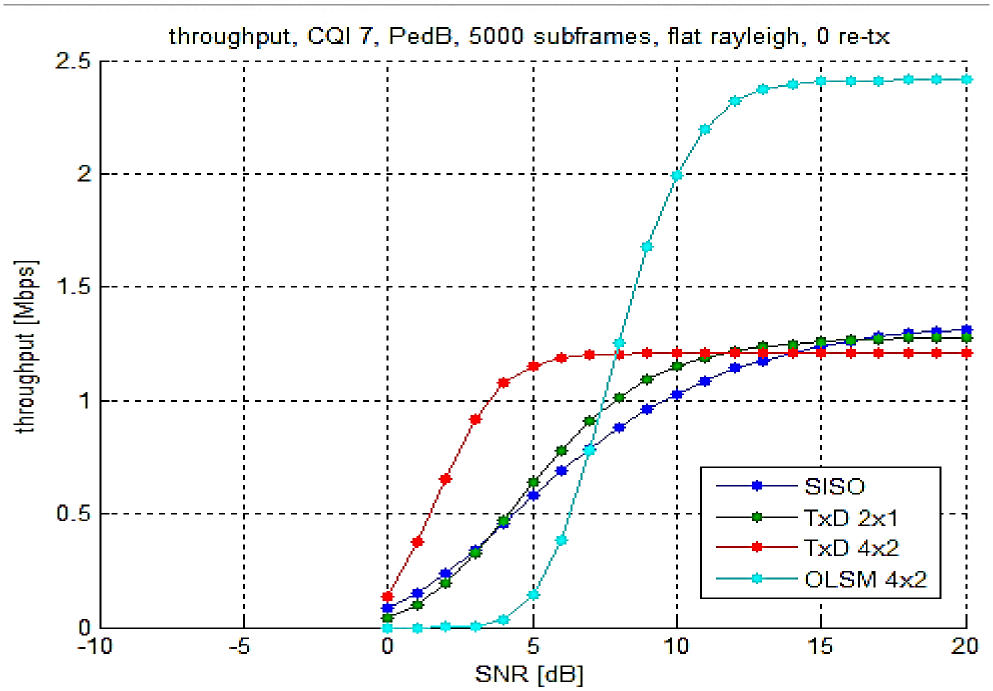

Figure 16 E-node B throughput flat Rayleigh channel

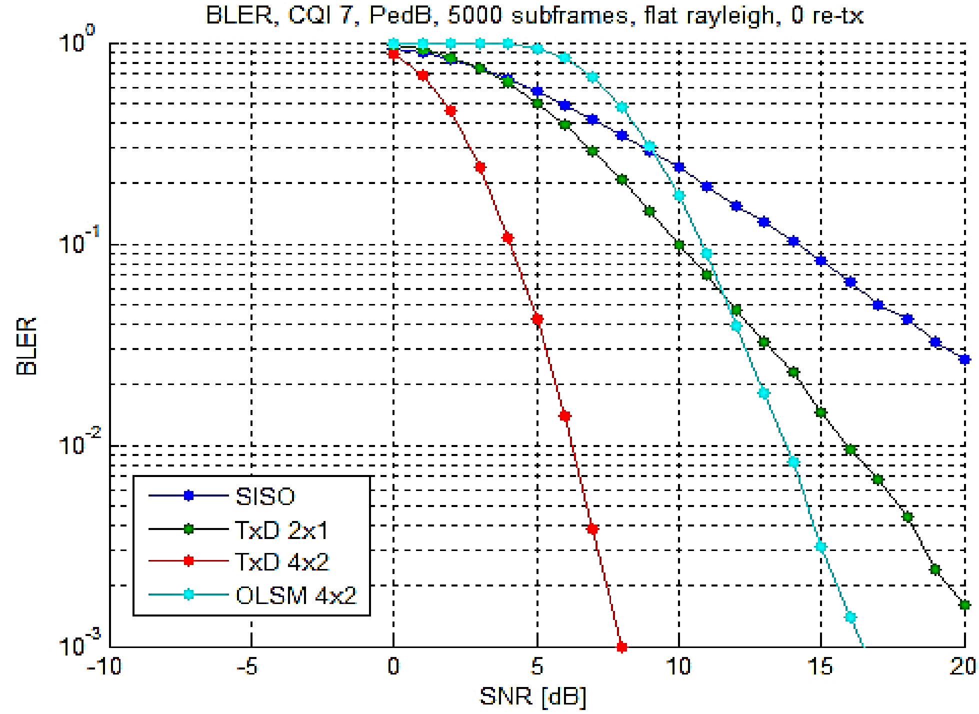

Figure 17 E-node B Block Error Rate flat Rayleigh channel

From Figure (9) to Figure (16), they show the performance of the system using Round Robin scheduler. The performance shown in Bit Error Rate and Cell throughput reading with spectrum of Signal to Noise Ratio SNR. These plots show the stability/reliability of the network. But, the cell throughput 2.5 Mbps at max is really low comparing to the other schedulers as shown below for the same circumstances shown in table (1) Environment Criteria.

3.4.2. Weighted Round Robin Scheduler (WRR):

The Weighted Round Robin scheduling started to be implemented more often, immediately after the ATM protocol lunched. Now WRR is under demand in some cell networks.

The Weighted Round Robin scheduling has been designed to better handle services with different processing capacities. Each server can be assigned a weight, an integer value that determine the processing capacity[46] [47]. Users with higher weights receive more connections than those with lower weights; subscribers with higher weights receive new connections first, while those with lower weights, and users with equal weights get equal connections. The next diagram provides an example of the WRR:

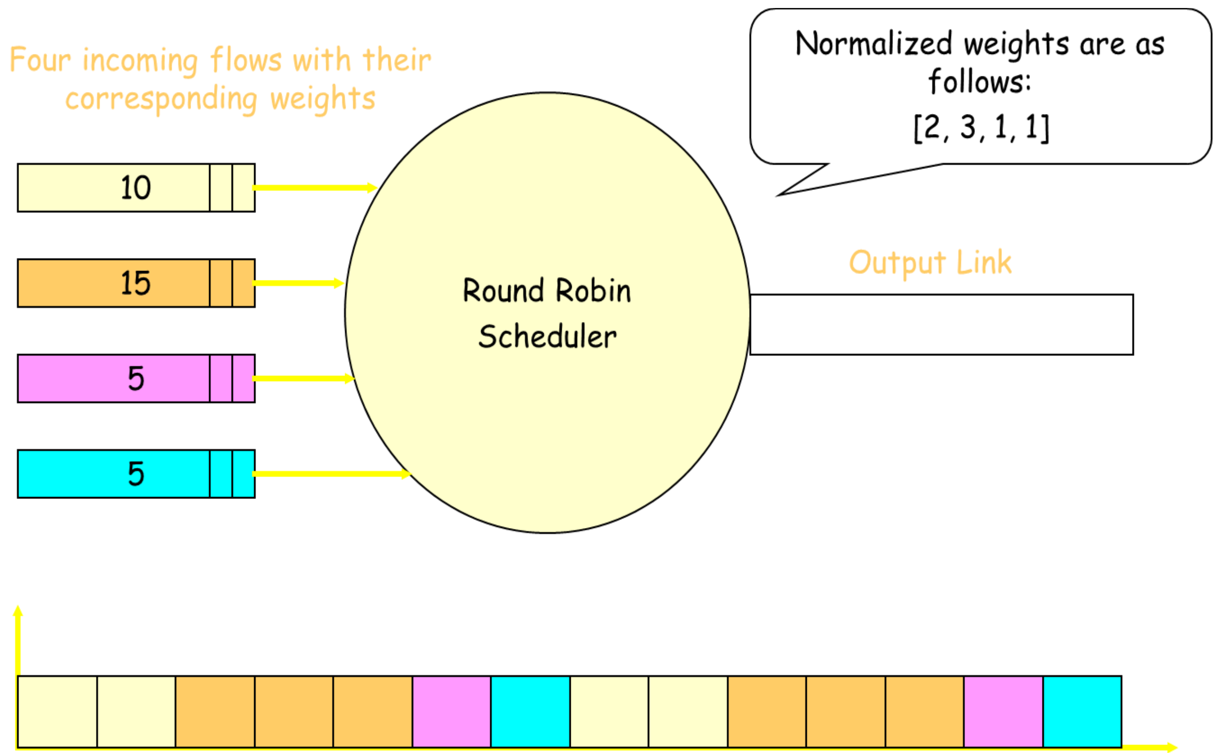

Figure 18 Weighted Round Robin Scheduling

In this example the normalized weights are [2,3,1,1] for the users [yellow(Y), orang(O), pink(P), blue(B)] . So, the schedule sequence will be YYOOOPB YYOOOPB for two sequential slots.

The Weighted Round Robin scheduling is way better than the Round Robin when we have stable user performance and their performance is not changing rapidly with time. Therefore, if subscriber behavior is changing rapidly and competitively with time the Weighted Round Robin will not improve the network's performance. It is for this reason we are representing our novel technique which is dynamic and uses the updated feedback from the channel situation from the previous sent TTI.

3.4.3. CQI_max Scheduler:

It is clear from its name the main key in this scheduling strategy is assigning the resources just with the users who have the maximum channel indicator. This means the strategy assigns resource blocks to the users with the best radio link conditions. The pilot signal that has been sent by UEs indicates the channel statues called Channel Quality Indicator CQI. Then the E node Base takes only the highest CQI's users or just the UEs in the best channel condition and sends them their packets through the channel, and the E node Base doesn't send other users packets. It is observable CQI_max scheduling algorithm will increase the E node Base capacity at the expense of fairness among users and stability of the individual. So, with using this algorithm, users located far from E node Base are unlikely to be considered in scheduling and this is real issue. The next figures showing simple diagram about how it works.

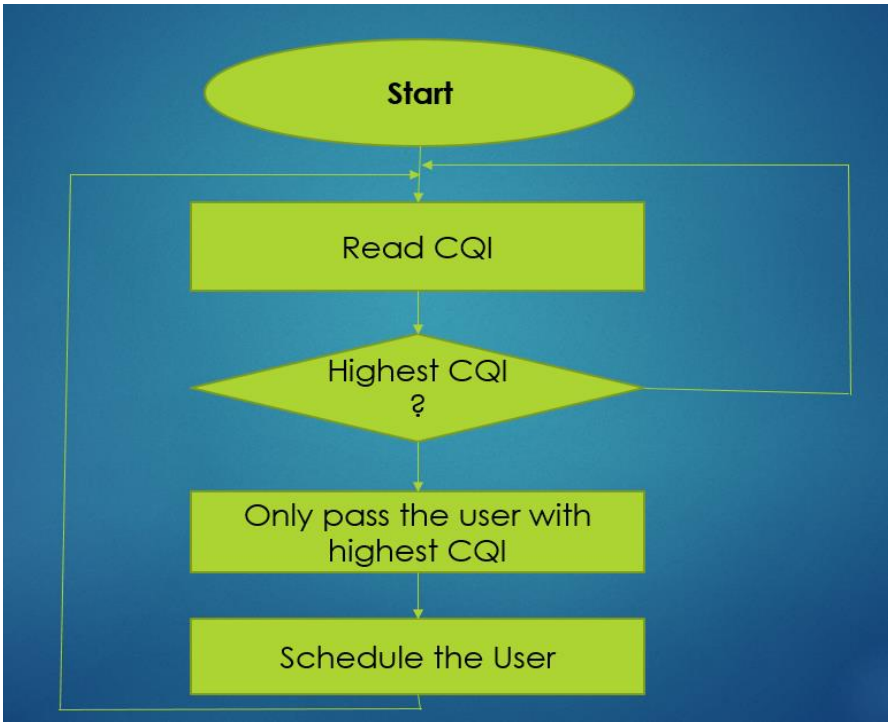

Figure 19 Best CQI scheduler flow chart

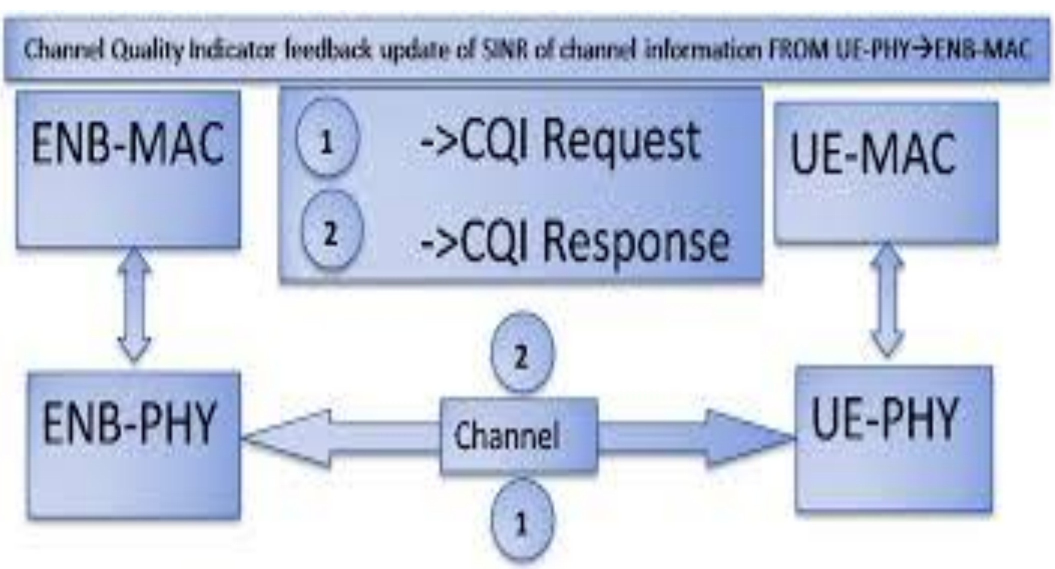

Figure 20 CQI Max Scheduler

We ran this scheduling algorithm in the simulation program within the same conditions as implemented in the previous Round Robin scheduler RR algorithm and indicated in table (1). We got these results plots for the performance for Flat-Rayleigh channel using CQI_max:

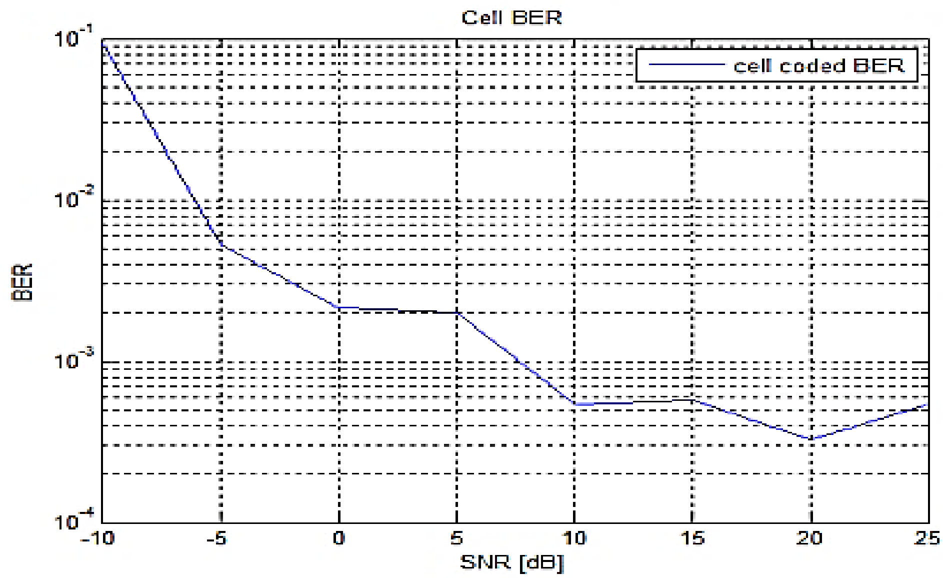

Figure 21 Block Error Rate for E-Node B

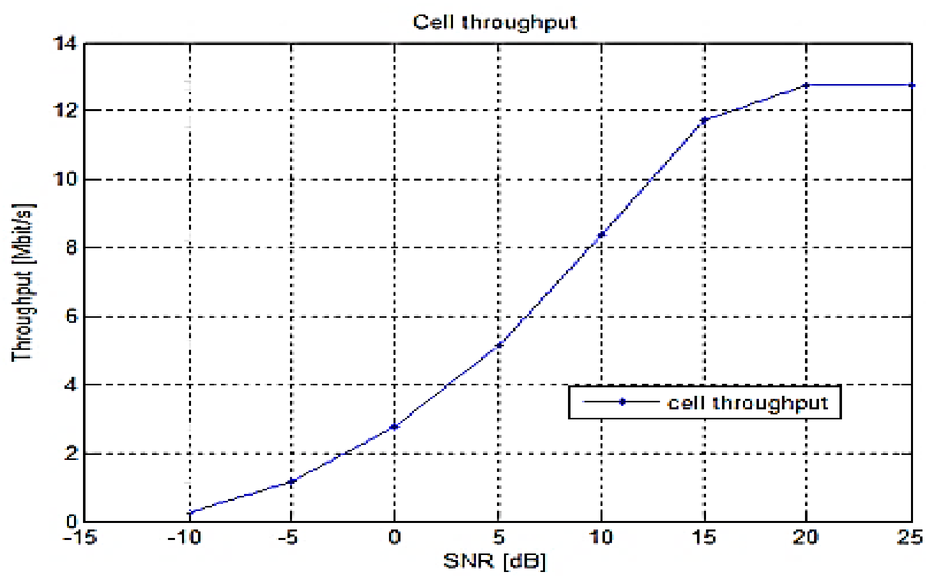

Figure 22 Throughput for the Cell

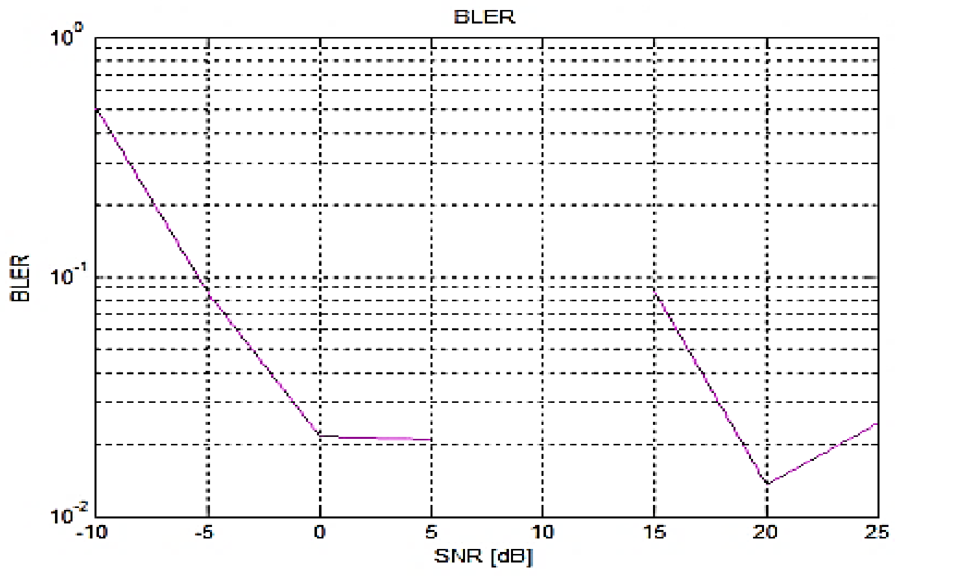

Figure 23 Block Error Rate User 3

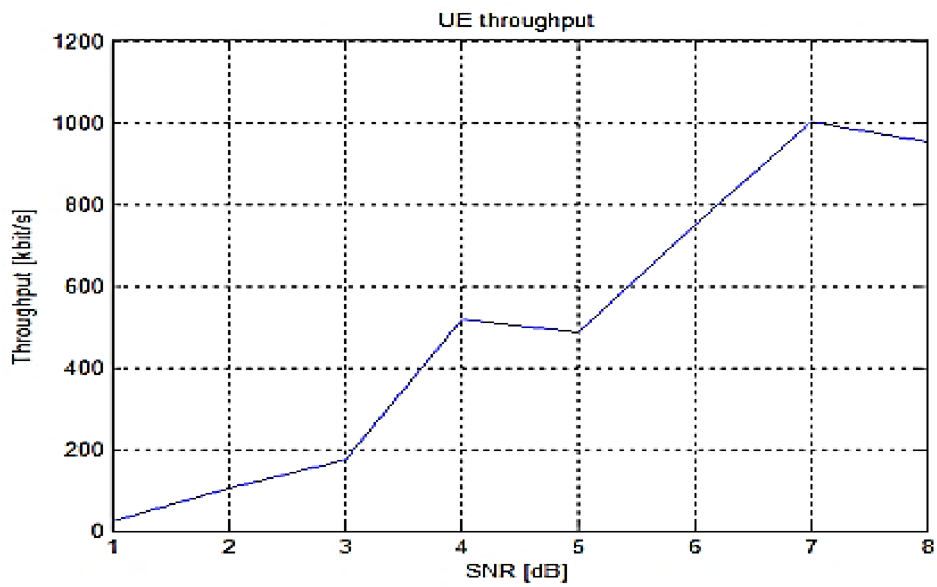

Figure 24 Throughput User 3

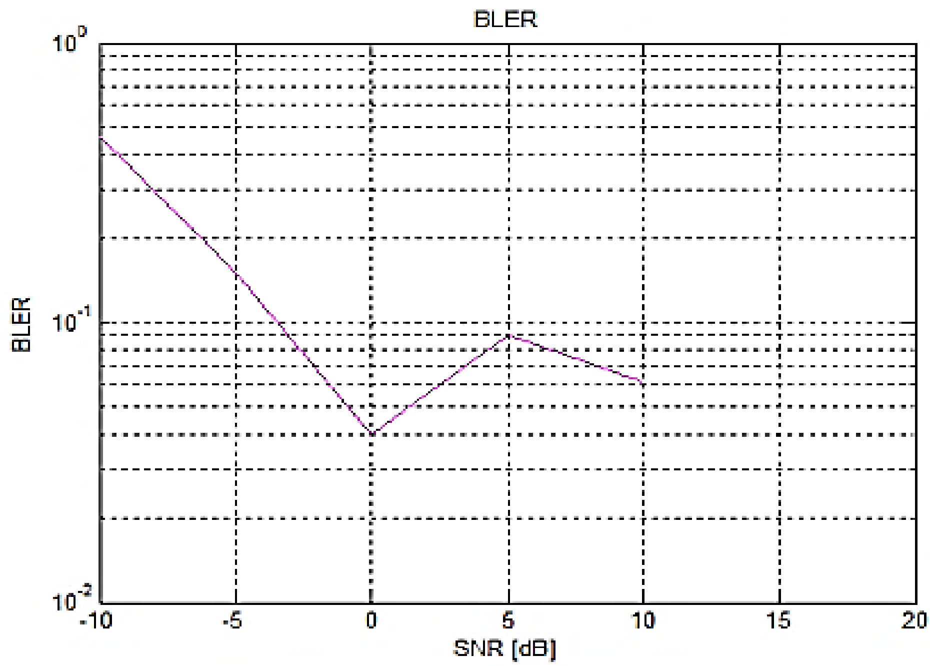

Figure 25 BL Error Rate User 10

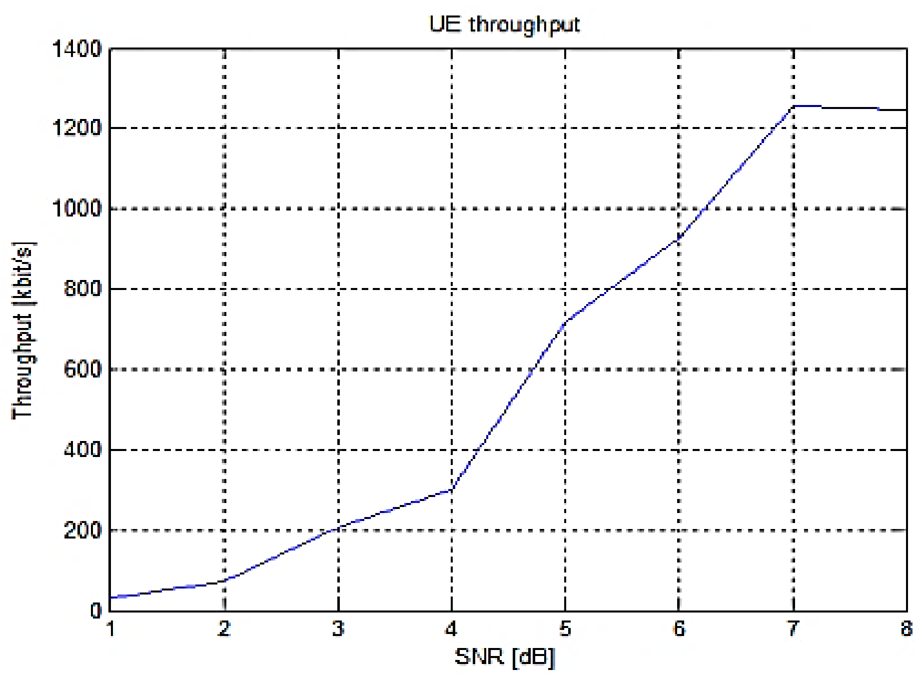

Figure 26 Throughput User 10

Starting from Figure (19) to Figure (24), these plots shows the performance of the system using CQI-Max scheduler, the performance are shown in Bit Error Rate and Cell throughput. From these plots it is observable the system not providing stability/reliability in the individual users point of view. As the sharp edges of the cell performance curves, and it is more clear in the individual Users performance plots as shown for User 10 and User 3. The discontinuity of the users performance showing the main reason of the delay, as at certain times in the curves the individual user was not included in the scheduling, this means the connection was diminished because its CQI feedback was weak (not the Max_CQI) during the time of discontinuity.

3.5. Novel Scheduling Algorithm (Self Organizing Neural Network Algorithm SONN):

3.5.1. Introduction about SONN Algorithm:

After deep review in the current publications that talk about Self Organizing in wireless networks, this with reviewing the performance of the scheduling algorithm with the new standard that LTE networks are offering into the resources (Time vs Frequency), which considered as a new unit in telecom industry and it is called (Resource Element). This new technique of sending/presenting the information accelerate the speed of the network in wireless networks by increases the capacity, as the capacity is one of the major challenges (Bottle Neck) in the wireless. However, sending the information with this method is needed to be smart of presenting it. In other words, mapping the information with certain way effects the speed of network by effecting the capacity of wireless channel. As LTE and LTE-A networks are smart and capable of providing feedback information to the E node Base from the user equipment UE about the channel situation in terms of Quality of Service (QoS), Channel Quality Indicator (CQI) and Signal to Noise Ratio (SNR).

3.5.2. Self Organizing Map (SOM) process:

The SONN technique we are introducing here has core algorithm browed from Artificial Neural Network called Self Organizing Map (SOM). Practically with implementing the main three steps of SOM with certain specific ways and functions:

3.5.2.1. How SOM is a competitive process:

From the beginning, we should have neurons vectors with same dimension as the input space.

As the input data is

$$X=[x_1,x_2,\ldots..,x_m]^T$$

From the other side the synaptic weight vectors, where the synaptic weight vector of neuron j be denoted by:

$$W_j = [w_{j1},w_{j2},\ldots,w_{jm}]^T, \quad j=1,2\ldots\ldots,L$$

L is the total number of the neurons in the networks. We are comparing the output of the multiplication of $W^T{}_j$ for the wholes neuron in the network and choose the highest value; we will take the indicators of the highest value. Here the only thing we really interested about is the indicator. Let's name i(x) as indicator. So, we can explain our calculation in the competitive process as:

$$i(X) = \arg\min \| X- W_j \|, \quad j=1,2,\ldots,l \qquad (3.1)$$

We are looking for the (i) which indicate the winner neuron $X_{i,}$ where X_i is the best matching neuron i. [7]

3.5.3. The Cooperative trait in the SOM process:

From the previous process steps, it is clear that the winning neuron is going to be updated by the input part. To make the other neurons effected by these input component. However, we should update the other neurons with less power than the winning neuron to get positive cooperation from them and this for fast convergence of the neuron network [113] [114] . To achieve these requirements:

The neuron locates to the center of a topological neighborhood of cooperating neuron should have the maximum coefficient and the others should get smaller coefficient where the neurons that excited with amount close to the winning neuron should have coefficient higher than the farther ones. It is clear that we are looking for a function decaying slowly as we are going far from its peak. We end up with function h_{ij} that denote the topological neighborhood centered on winning neuron (i) and excite neuron (j). the d_{ij} denotes the distance between the winning neuron (i) and excited or effected neuron (j). So, the function h_{ij} is unimodal function of the lateral distance d_{ij} which going to satisfy this conditions:

1- The topological neighborhood h_{ij} is symmetric about the maximum point defined by $d_{i,j} = 0$, here we try to say the winning neuron has zero distance of this function

2- The amplitude of topological function is decreases monotonically with increasing the lateral distance $d_{i,j}$, which decaying to zero for $d_{i,j} = \Theta$ this condition for convergence.

The typical function that applies these conditions is Gaussian function:

$$h_{i,j} = \exp\left(-\frac{d^2{}_{i,j}}{2\sigma^2}\right) \qquad (3.2)$$

the parameter σ in the last equation is independent from the distance $d_{i,j}$, and the parameter σ is called effected width of the topological neighborhood as illustrated in the coming figure; It is a measurement degree of effecting of each neuron in the update.

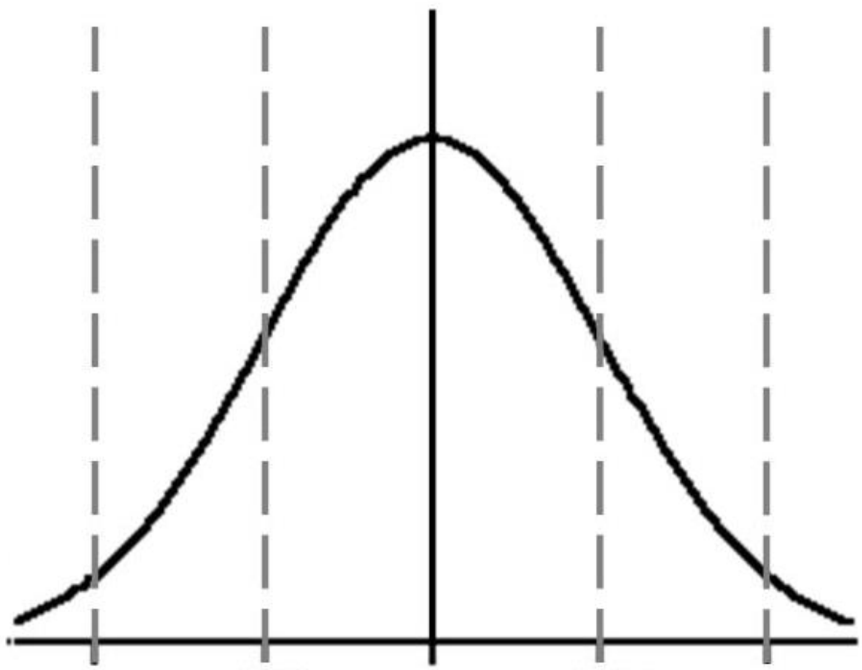

Figure 27 Gaussian Neighborhood function

Toward apply best cooperation we apply the distance in the neighborhood function $h_{i,j}$ is centered by the winning neuron and decrease as we get less value than the value of the winning neuron. The distance between winning neuron and the other neurons $d_{i,j}$, $d_{i,j}$ is an integer equal to |i-j|, and the case of two dimensional lattice it is going to be defined as:

$$d^2{}_{i,j} = \|r_j - r_i\|^2 \qquad (3.3)$$

The discrete vector r_j defines the position of excited neuron j and r_j defines the discrete position of winning neuron i, both of which are measured in the discrete output space.

SOM has lot of unique features in its algorithm; one of these features is the control it has on the width of the topological neighborhood function especially it is shrinking with time. This feature helps a lot to keep the network instable situation after it reaches to the convergence period.

This leads to make σ be function of time. Therefore, we can write it as:

$$\sigma(n) = \sigma_o \exp(-\frac{d_{j,i}^2}{\tau_1}) \qquad n=0,1,2,3……,$$

(3.4)

Where σ_o is the initial value of σ at initial SOM algorithm, τ_1 is a time constant. With using, the last distribution of σ and the neighborhood equation become:

$$h_{j,i(x)}(n) = \exp(-\frac{d_{j,i}^2}{2\sigma^2(n)}), \qquad n=0,1,2….,$$

(3.5)

All the component of the previous equation is well known where the time (n) is equal to number of iteration, and it is clear the width is decrease with the time as σ(n) decrease exponentially so, the topological neighborhood function will response with similar way.

With having wide width of neighborhood function at the beginning will help most of the neuron be effected by the update then the decrease of the function will help a lot on the correlation function to stay converged to certain value.

In most of computer programs that using the SOM are using normalizing technique and it is called renormalized SOM from the training. According to which we work with a much smaller number of normalized degree of freedom. This operation is easily performed in discrete form by having a neighborhood function $h_{j,i(x)}(n)$ of constant width, but gradually increasing the total number of neurons. The neurons are interested halfway between the old ones [7].

3.5.4. Novel Adaptive Process

It is well known that the Self Organizing Map (SOM) is a neural network. At the last stage of the adaptive process, the synapsis w_j that belongs to the neuron (j) should be effected by the input data (x). The main target is presenting the effect that x can apply to different synaps. As the SOM is an unsupervised learning algorithm so the updating process automatically can be done proportionally to the input (x) as:

$$\Delta w_j = \eta \, y_j \, x + g(y_j) \, w_j \qquad (3.6)$$

This is the general presentation for the effect of the data on the synaptic. The main parameter that effects the update value is the step size η. η is the learning rate parameter that the synaptic will be effected by the input data, and y_j can be applied as the function talks about the response we have for any kind of input data, where both $g(y_j)$ and y_j are just correcting factors,

$$y_j = h_{j,i(x)} \qquad (3.7)$$

The previous equation (3.6) can present the update changing value of each step as:

$$\Delta w_j = \eta \, h_{j,i(x)}(x - w_j) \qquad (3.8)$$

After we understand the increment that is effected by the input data which should be added to the previous weight at each instant, we can see the big image for the weight's reaction as:

$$w_j(n+1) = w_j(n) + \eta(n) \, h_{j,i(x)}(n)(x(n) - w_j(n)) \qquad (3.9)$$

The equation (3.9) will be applied for all neurons fond in the lattice as a neighborhood function. But, it is going to affect each neuron with a different value depending on each location of the winning neuron. The winning neuron is going to be updated with a complete factor or multiplied by value (one) and the others will be effected proportionally, depending on how far the complete matching is from the input data in the current iteration.

The process keeps running and using the previous equations once at each TTI, and after each TTI the process ends up with a grid of the whole neurons. The grid explains the historical input data over all previous TTIs with a small number of neurons presenting this historical Channel Quality Indicators (CQIs) feedbacks.

The updated weights function depends on a lot of functions as well. One of these functions is $h_{j,i(x)}$ which is a heuristic function, and explains the neighborhood behavior for the whole neuron compare to the all input data. The other heuristic function is $\eta(n)$ where our learning rate function depends on the history of the input data.

The learning rate non-linear function $\eta(n)$ is a function and with the time with initial value η_o which is proportional to time increasing toward converging the mod-SOM algorithm, $\eta(n)$ can be expressed as:

$$\eta(n) = \eta_o \exp(-\frac{n}{\tau_2}), \qquad n=1,2,3\ldots.., \qquad (3.10)$$

You can see the learning rate is decaying with time, and it has a living time where it is going to maintain stable response for a while then will start decaying, this means we have complete control in change function [88] [112].

As the learning rate is changing with time, it is traveling through two main phases during the whole SOM process:

- **Modification done to Self-Organizing Map (SOM):**

This is one of the main contributions in this work. we are using a modified form of updating the weights. In this novel algorithm the updated weights are energy based and the updated function including the non-linearity. This helps our case, as we want to do mapping with clustering in one direction.

As in the coming equation we will deal with the energy instead of the regular Euclidean Distance or Kullback-Leibler Distance:

$$E_j = \frac{1}{4} \left[\sum^N (X_l(n) - W_{j,l})^4 \right] \qquad (3.11)$$

In the next steps we compute the winning neuron which is the winning Channel Quality Indicator (CQI) feedback that presents the UE in the algorithm:

$$i(x) = \arg\min_j (E_j) \qquad (3.12)$$

Then, we updated the "winning" neighborhood as:

$$\Delta W_K(n) = \eta(n) h_{ik}(n)\, \delta/\delta w_K (E_j) \text{ for } K \epsilon N(i)$$

$$\Delta W_K(n) = \eta(n) h_{ik}(n) (X(n) - W_k)^{\mathbf{3}} \text{ for } K \epsilon N(i) \qquad (3.13)$$

This modification really needed to be done, as the algorithm was working from the beginning starting from the first TTI. We are using the output of the beginning output of the results as regent and the sold output is needed even in the warming up period (before the convergence).

This modified updating is smoothing the values of the weights at each TTI, and the price is slower to converge the weights which are visible for our case here.

3.5.5. The Self Organizing Neural Network (SONN) algorithm LTE Scheduling Section:

As in this algorithm SOM technique is the core or the key function in the process. The SOM algorithm can be explained in clear steps, With these clear steps we can summarize the Kohonen's SOM algorithm and understand the main functions that SOM algorithm can be applied for. Kohonen's SOM algorithm substitutes a simple geometric computation for the more detailed properties of Hebb-Like rule and lateral interactions. The main vision for the algorithm can be summarized as:

A continuous input space of activation patterns that are generated in accordance with a certain probability distribution. A topology of the network is in the form of a lattice of neurons, which gives discreet output. In other words, one of main uses of the SOM algorithm is to change a continuous input data to discrete output data with another presentation.

The SOM algorithm is using a new technique by applying a time varying neighborhood function for the winning neuron i(x) which will update the neighbors neurons and has close values to the winning neuron. This will be updated but with smaller values depending on how far it is from the winning neuron.

One of the important parameters in the SOM algorithm is the learning rate parameter $\eta(n)$ that starts at an initial value η_o and then decreases gradually with time, n, but never goes to zero.

Those are the main steps we can explain more about one of the main parameters on the algorithm which is the neighborhood function, and can be used when applying the next two equations immediately in sequence:

$$H_{j,i(x)}(n) = \exp\left(-\frac{d_{j,i}^{2}}{2\sigma^{2}(n)}\right), \qquad n = 0,1,2 \qquad (3.11)$$

$$\eta(n) = \eta_0 \exp\left(\frac{n}{\tau_2}\right) \qquad (3.12)$$

One of the main need for applying these equations to make sure that η(n) would maintain small values like 0.01 during the convergence period which going to be after long iterations.

The other noticeable way to apply the algorithm is dealing with small neighborhood function even single effected neuron at the earlier first steps and wider at the last ones.

In general, we can summaries the SONN algorithm as:

1) Initialize each node's weights: this can be done by choose random values for the initial weight vectors $w_j(0)$. The only restriction here is that the $w_j(0)$ be different for j=1,2,3…,l where j is the number of neurons in the lattice. It may be desired to keep magnitude of the weights small. The other way to initializing the algorithm is to select the weight vectors $\{w_j(0)\}^{l}_{j=1}$ from the available set of input vectors $\{x_j\}^{l}_{i=1}$ in random manner.

2) Every node is examined to find the Best Matching Unit of the weight vectors.

This step called sampling, draw a sample x from the input space with a certain probability; the vector x represents the activation pattern that is applied to the lattice. The dimension of vector x is equal to m.

3) Similarity matching. find the best " winning" neuron i(x) at time step n by using the minimum distance Euclidean criterion :

$$i(x) = \arg\min_j \|x(n) - w_j\|, \quad j = 1,2,\ldots\ldots l \qquad (3.13)$$

so, here at SOM we are exciting about the rank of the winning neuron to update its value. Then, the radius of the neighborhood around the weight vector is calculated. The size of the neighborhood decreases with each iteration.

4) Each weight and its neighborhood has its weights adjusted to become more like the wanted shape for the SOM weights. Nodes closest to winning neuron are altered more than the nodes furthest away in the neighborhood. Here is the updated rule:

$$w_j(n+1) = w_j(n) + \eta(n)\, h_{j,i(x)}(n)(x(n) - w_j(n)) \qquad (3.14)$$

where $\eta(n)$ is the learning–rate parameters, and $h_{j,i(x)}(n)$ is the neighborhood function centered around the winning neuron $i(x)$; both $\eta(n)$ and $h_{j,i(x)}(n)$ are varied dynamically during learning for best result.

5) Repeat from step 2 for enough iterations for convergence.

6) In terms of modification, we can use equation (3.14) with odd power to the deference, as in our case, we use the energy in eqn (3.11). Then, the weight update will converge faster and provie quick results. In that case, the update law becomes:

$$w_j(n+1) = w_j(n) + \eta(n)\, h_{j,i(x)}(n)(x(n) - w_j(n))^3 \qquad (3.15)$$

7) In terms of modification, we can use convex sum technique by averaging the effect of each winning neuron. And that going to be implemented as well in chapter 5.

This is summarized below as Algorthim1:

Algorithm 1: Energy Based SOM Algorithm

1:**Procedure** INITIALIZATION

2: W ← Initializing the adaptive weights

3: X ← Fetch the vector of Indictors for the 1st TTI

4:epoch ← Number of epoch

5: α ← Step size

6: $\text{ɟ}(x) = x^3$ ← Final Shape pf the non-linear function

7:Processing the loop

8: Computational part

9: $E_K = ¼ [\sum(X_l(n) - W_{j,l})^4]$

10:$i(x) = arg\ (min(j))E_j$ for all j

11:Updating part

12: $\Delta W_k(n) = \eta(n)h_{ik}(n)(\delta/\delta w_K)(E_j)$

13: $\Delta W_K(n) = \eta(n)h_{ik}(n)(X(n)-W_k)^3$ For $K \epsilon N(i)$

14: Close

Algorithm 1 will be called at each TTI = 10ms by algorithm 2 as it is responsible for the management and for clustering the Channel Quality Indicator CQI feedback time-sequence.

3.5.5.1. SO Scheduler Algorithm Framework:

The design of the Downlink scheduling algorithm, this link is between the E Node Base as source and User Equipment as destination. This scheduling algorithm is complex procedure and it have a number of design challenges, for example maximizing the system capacity and spectral efficiency, fairness approach, bit error rate etc. This report presenting new approach for a such algorithm that handle all these challenges with providing optimum algorithm. As the OFDM parameters (Resource Element), timing and frequency settings, channel quality feedback and channel quality indicator (CQI)) standardized according the 3GPP standards. Therefore, the main principle of the scheduler in LTE and LTE-A is dynamically determined every 1ms interval which usually one Transmission Time Interval (TTI). The main rule of this algorithm is to get advantage of all information we got from the feedback in the previous TTI and make the mapping of the coming TTI as similar as it makes.

This scheduler is dynamic scheduler like Best CQI scheduler. But, this one is a way more optimum than the best_CQI_ scheduler as MSOM putting in consideration all the users in counts and it trial to map the users as the environment treated them in the previous TTI. Each user faces different channel conditions at a given time. At any given time, there will be high probability that some users will have good radio link condition.

This Mapping will be done to the CQI parameters we got through the feedback for the previous TTI and it will be done by Self Organizing Map (Artificial Neural Network) to these CQI , so after we got the best mapping of CQI in values and indicators of users, the algorithm will use the mapping of the indicators to schedule the users into the Resource Block. With this way most of the users get chance to receive data this grantee the fairness and vanish the latency that could happen because of scheduling, and the users of best CQI got the biggest part of resource block, which will enhance the overall throughput. Putting the overall procedure into steps:

- 1) Get the CQI_Feedback matrix of the previous TTI, these CQI values should have indicators to the users on each one of them.

- 2) Find the mapping of these value in the CQI_Feedback relating to the Maximum CQI_feedback using Self Organizing Map (ANN) Matrix and corresponding user.
- 3) Now the algorithm should map the users to this feedback information. In addition, Schedule that user in that RB.
- 4) The schedule grid scan the mapping if there are user or more not in the map: It will take RBs from the most repeated users to sign them to missing users one time.
- 5) Until the end of the TTI, this user will not have permission to be scheduled. With the TTI finish so we will release this schedule to be applied.

This Novel schedule provides a way better result in terms of network throughput as well as it gives a way better performance of UE throughput and UE latency. As it is providing UE with better channel environment main priority as well as it provides the UEs with poor channel quality spots in the Resource Blocks of the mapping. In general speech, this algorithm dynamically adjusts the transmission rank, precoding matrix indicator and channel quality indicator according to the feedback (if present). Afterwards it schedules users proportional to their theoretically attainable rate (as the true one is not known)

This algorithm are maintain to apply a certain fairness into mapping by at least provide one resource block RB to users even if there are zero values Channel Quality Indicator CQI for them. This Sub-rotini added to make the algorithm not that greedy with CQI.

This is the Algorithm 2:

Algorithm 2: Self Organizing Scheduler

1:**Procedure** FETCHING

2: Find the UE feedback of the previous TTI

3: CQI ← Build the UE matrix of the previous TTI

4:Itr ← Assign Number of Iteration

5:THD: Eliminate UE with CQI below the threshold

6: $f(x) = x^3$ ← Final Shape pf the non-linear function

7:Processing the loop

8: SGN ← Assign the group needed to be mapped

9:Call ***Energy Based SOM*** Algorithm for execution

11:Wait TTI to be finish, no schedule permitted…..

12: @ End of TTI, Release the scheduling map

13: Close

It is clear Algorthim2 is showing the superposition method of the user mapping into the Resource Blocks RBs procedure. Step 3 in Algorithm2 will have more details in the next highlight.

3.5.5.2. SONN Scheduler Algorithm Mapping:

This section contains the details of step number 3 on the **SO scheduler Algorithm framework**; this step has a novelty way of mapping which provide stability and accelerate the process of scheduling all this has been provided based on the statistic distribution of the clusters of the Channel Quality Indicators CQI of the users. This has been done with using non-linear function SoftMax function. This step really make the scheduling process faster and made a such a hierarchy to the scheduling process helps toward managing the users into the resource blocks RB grid, this matters a lot when the cell dealing with large number of users. As dividing, the users into clusters based on their statues on the historical CQI which is the pattern of the users give the decision easier to be taken and implemented.

Practically, Step 3 in the **SO Scheduler Algorithm Frame** is called the **Novel Mapping Algorithm of the Clusters** and it receives the users distribution inside clusters (groups) based on the historical CQI over the all previous time (all previous TTIs). The **Novel Mapping Algorithm of the Clusters:**

1- Fetch the clustered (grouped) Channel Quality Indicators (CQI) of the users and name all of them

2- Provide SoftMax non-linear function to each cluster. So, each cluster will have class accordingly

3- Map the clusters proportionally based on its SoftMax value to the Resource Blocks RB grid

$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \quad \text{for } j = 1, \ldots, K. \tag{5.14}$$

So choosing the clustering and ranking them will be probabilistic based not just a signed value criteria, this provide us with more robustness and adoptability to the pattern.

4- Distribute the users in each class equally to the RBs portion of their class to provide kind of fairness

5- Print the map of this TTI

The process in step 3 at algorthim2 could be summarized to:

Algorithm 3: SO Scheduler Algorithm Mapping

1: **Procedure** FETCHING

2: Clusters ← Group CQI feedbacks by Algorithm 1

3: SoftMax ← Each cluster highlighter by non-linear fun

4: **Procedure** Processing the loop

5: Mapping the Cluster proportionally with SoftMax value

6: SGN ← Assign the group needed to be mapped

7: DST ← Distribute UEs in same Cluster equally

8: Classes ← Build the UE matrix of the previous TTI

9: Wait TTI to be finish, no schedule permitted…..

12: @ End of TTI, Release the scheduling map to step4 in Algorthim2

13: Close

In this algorithm, we provide proportional fairness of scheduling. This is clear and has been provided by step number 4. the users in the same class has been provided the same number of resource blocks even though they could have a different CQI. This happens with maintain providing the priority to the users with the high CQI and higher number of RB. This algorithm will be important with in a situation with a cell connecting with too many users.

3.5.5.3. SONN Scheduler Algorithm Performance:

The figures below describe the great performance of this algorithm:

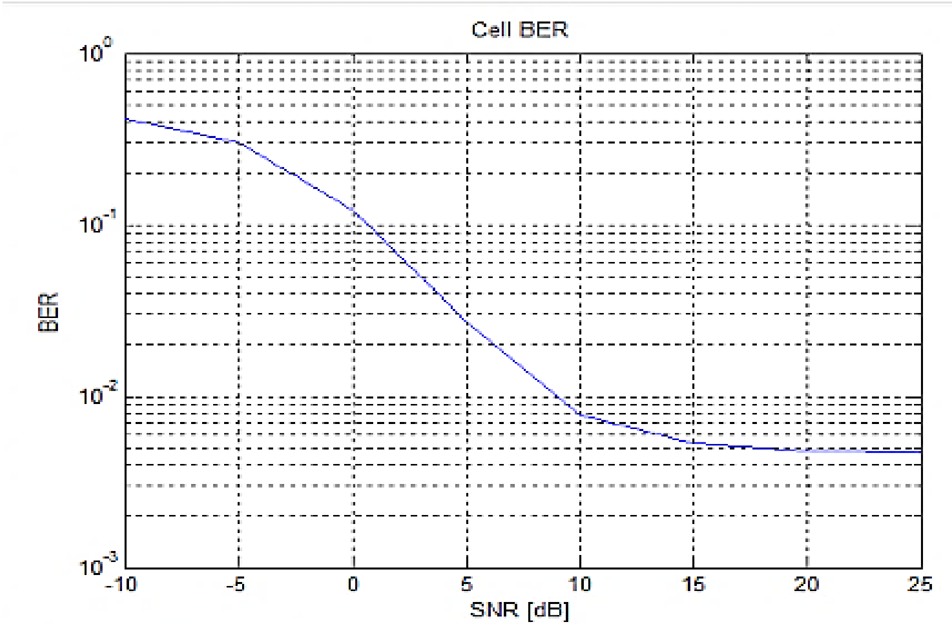

Figure 28 Block Error Rate for the Cell

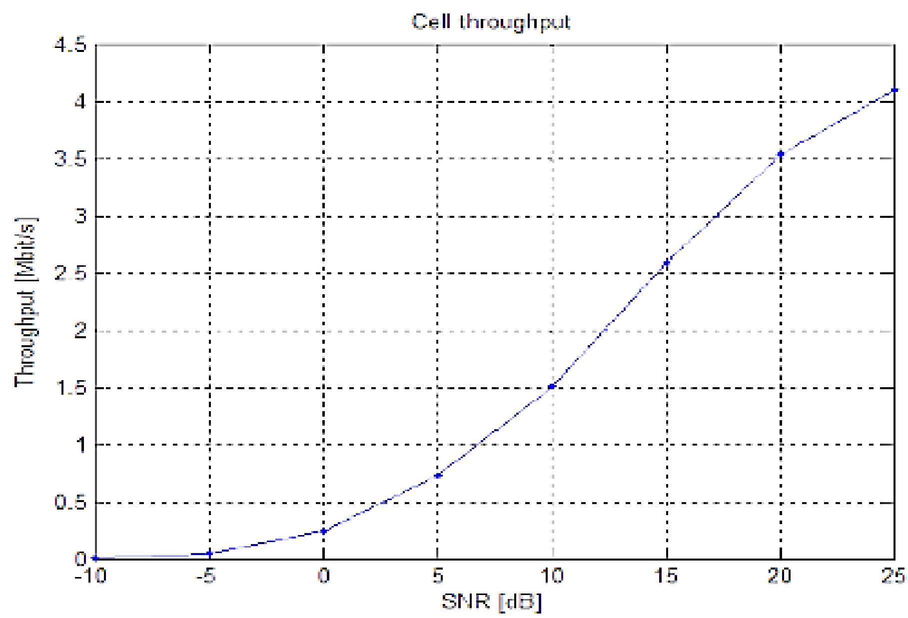

Figure 29 Throughput for the Cell

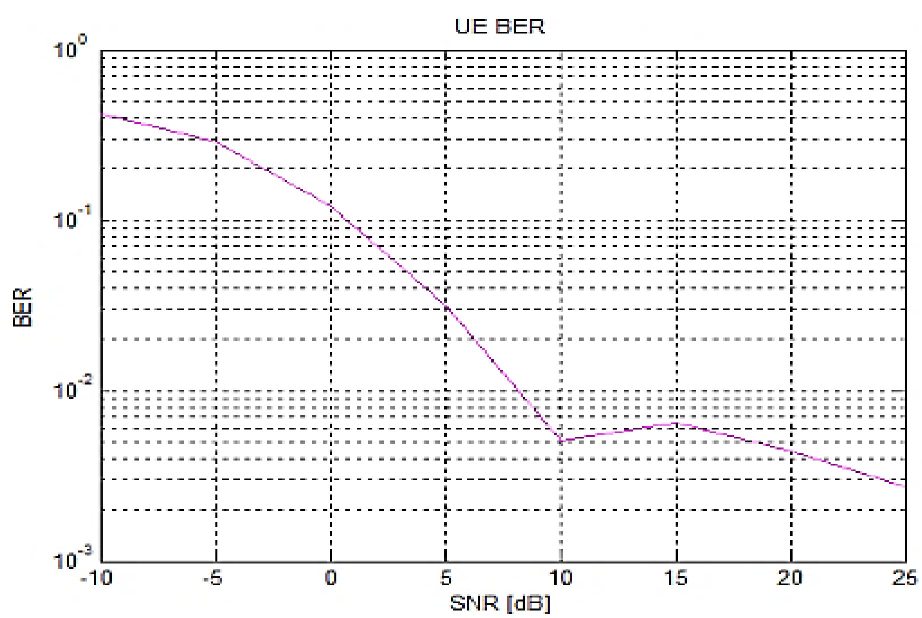

Figure 30 Block Error Rate for User 3

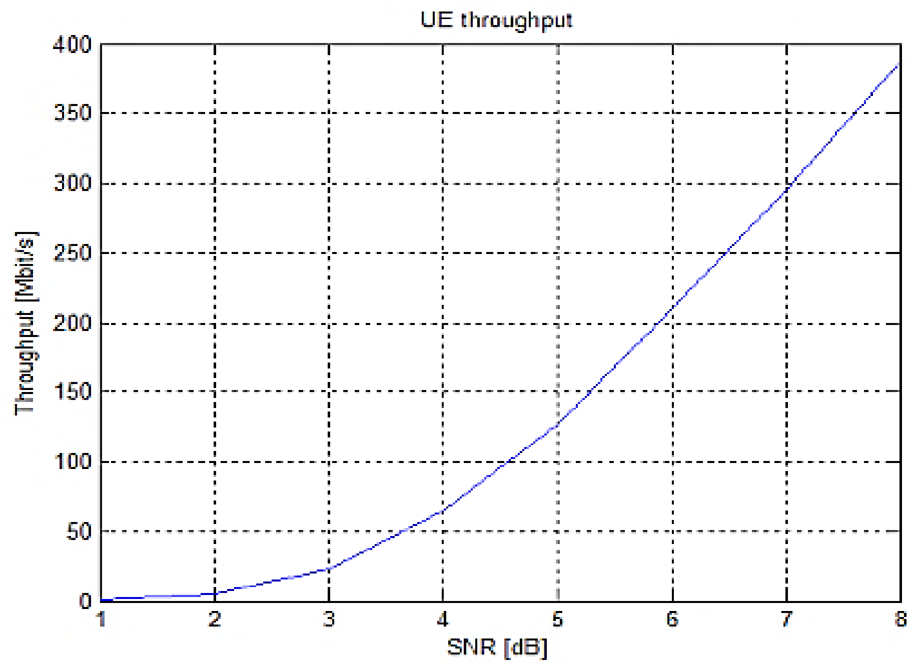

Figure 31 Throughput for User 3

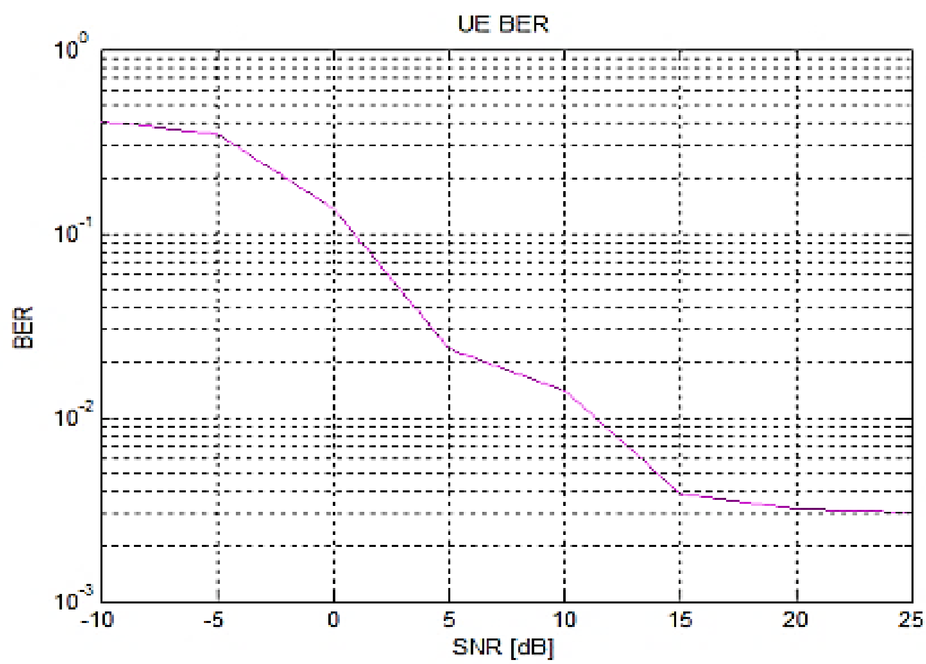

Figure 32 Block Error Rate for User 10

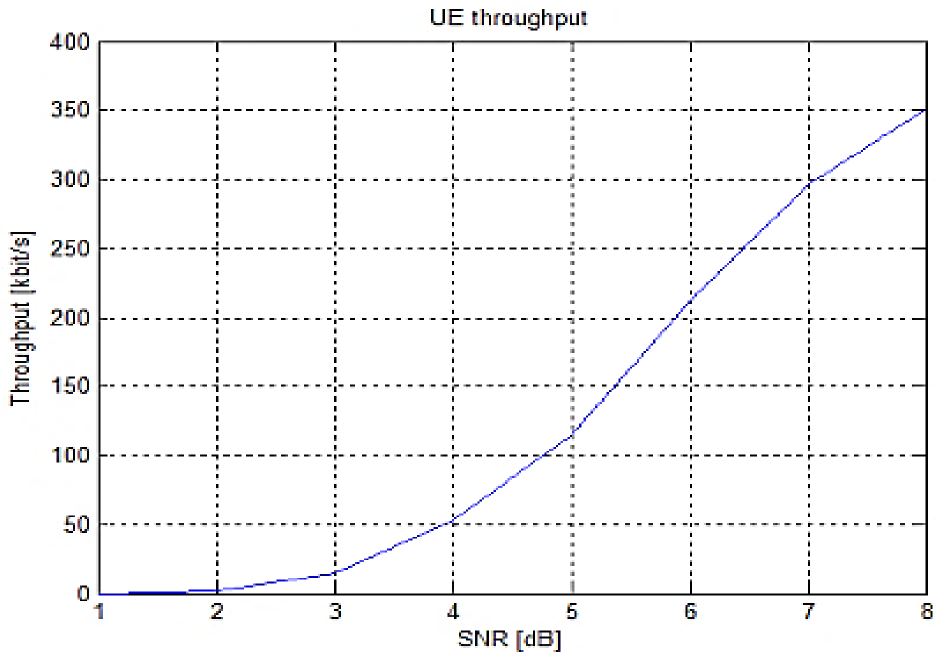

Figure 33 Throughput for User 10

From Figure (25) to Figure (30) shows the performance of the system using the Novel modified-SOM scheduler algorithm(SONN). The performance shown in Bit Error Rate and Cell throughput. From these plots it's observable the system is providing stability/reliability in the individual Users point of view. As there are no sharp edges in the curve showing in the cell curves and it has, more clear in the Individual Users plot like User 10 and User 3 they have high smooth curves over all the period.

All these outcomes have been provided with arrangements of random process among all normal for the strategy. As the Matlab Simulation Box give us an irregular arrangement of all sub documents such is the channel modeling and ecological sets. We furnished this procedure with finish diverse situations and we wind up with strong outcomes in a similar grouping, for example figure 34, to figure 38.

- As the main challenge is how we can trade-off between increasing the E Node B throughput and provide fairness between the users:

3.5.6. Fairness evaluations among several scheduling process:

Jain's fairness index is adopted for the evaluation of the user fairness performance to define the degree of fairness among users. Mathematically, the fairness index can be expressed as follows [18].

$$\mathcal{J}(\mathrm{x}_1, x_2, \ldots\ldots, x_n) = \frac{\left(\sum_{i=1}^{n} x_i\right)^2}{\mathrm{n}\sum_{i=1}^{n} x_i^2} \quad (3.15)$$

where (n) represents the total number of user, (x_i)represents the throughput of individual user (i) and $\mathcal{J}(\mathrm{x}_1, x_2, \ldots\ldots, x_n)$ represents the fairness among the n end users. For this part, simulation parameters and assumptions are the same as Table 1. The spectral efficiency performance and the fairness performance of these schedulers are shown in figure 37. From figure 37, it can be observed that the RR scheduler provides the best fairness. But, as shown in figure RR has least spectral efficiency performance. In contrast, the Max-CQI scheduler provides the best spectral efficiency. But, the worst fairness performances as shown in figure16. The spectral efficiency has been quantified in this work by the throughput measurements.

We have compared the performance of SONN algorithm verses the well-known existing benchmark algorithms, namely, the Round Robin (RR) and the CQI-max algorithms, on the cell throughput criteria. Figure34 depicts the resulting the cell throughput versus SNR for all three different scheduling schemes.

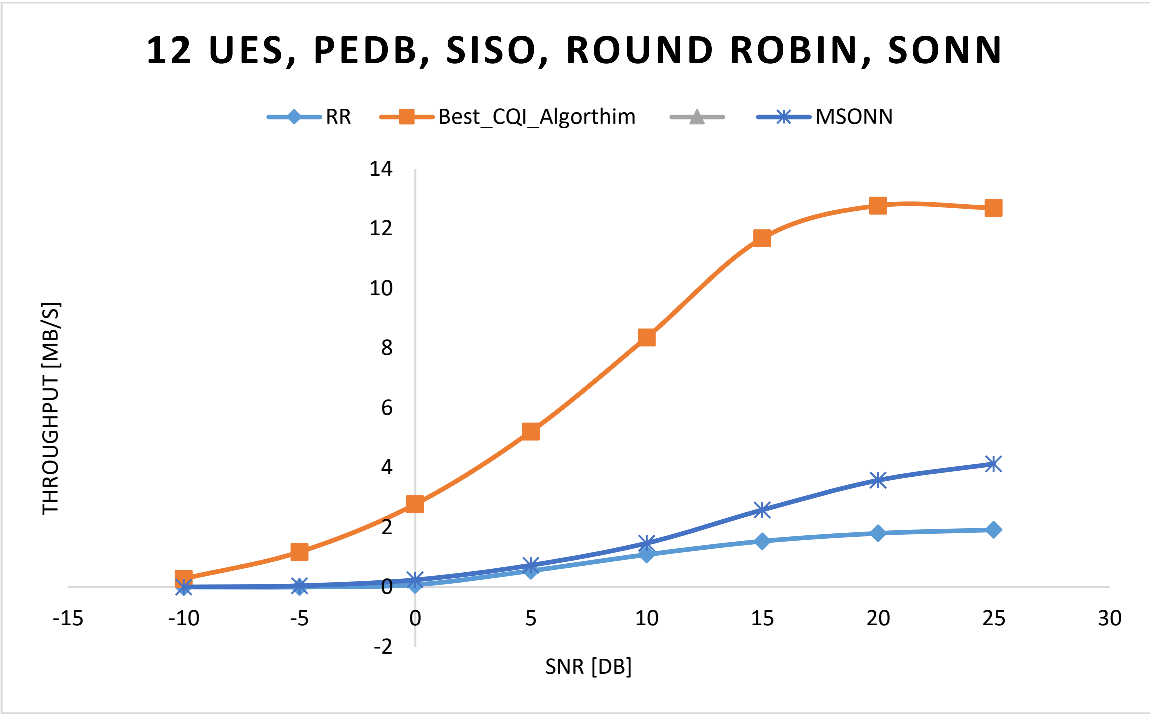

Figure 34 Cell throughput for the three different scheduler schemes.

It is noted that the RR scheduling performance is the worst in the throughput measurements, since it does not consider the user channel condition into account. The CQI_max scheduling achieves the highest overall throughput in the example but at the expense of the notion of "fairness" to all users. As depicted in Figure 35, the new SONN algorithm is providing a trade-off between the throughput and fairness to all users. and in figure34 its throughput performance is in the average scope. After normalizing the throughput performance among all different types of schedulers, we got the metric of figure 36. This metric will be applied for overall performance.

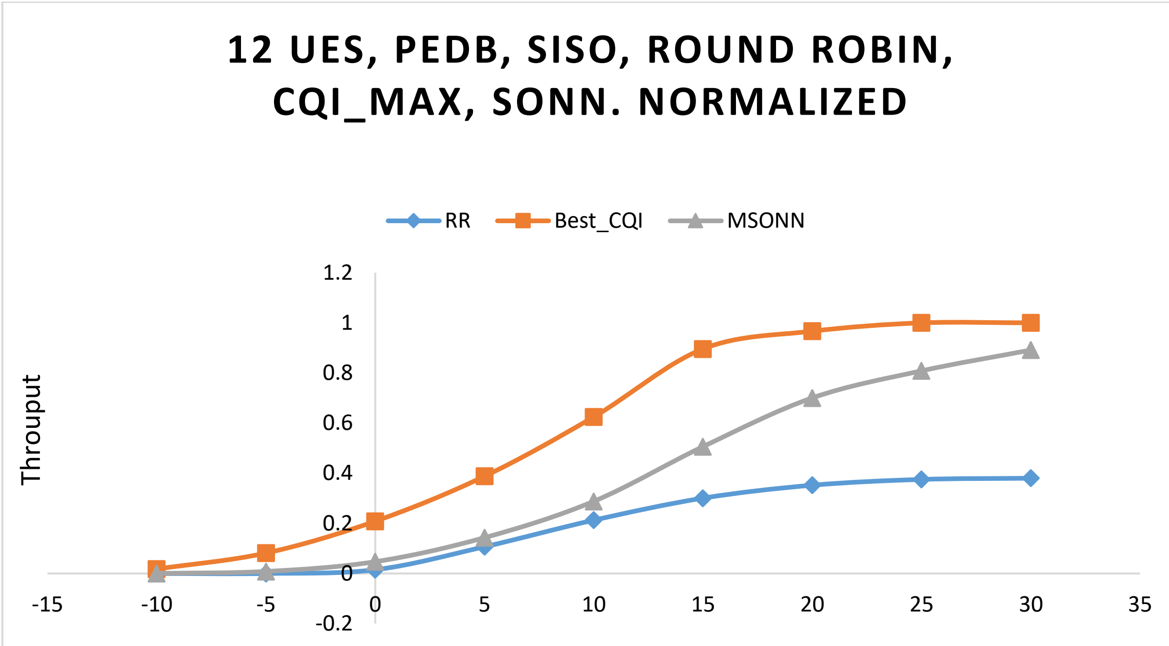

Figure 35 Normalized cell throughput for the three different scheduler schemes.

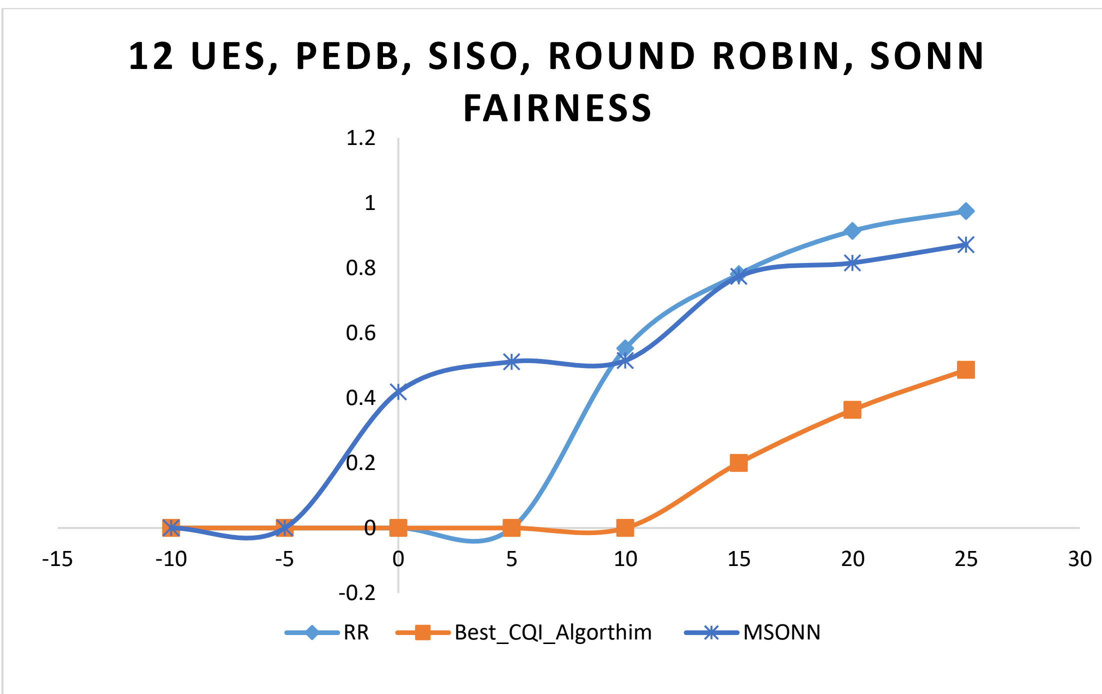

Figure 36 Fairness among users for the three different scheduler schemes.

Toward a full comparison of all algorithms performance, we end up with matrix that represents the normalized sum of throughput matrices and fairness matrices in the evaluations. Figure37 depicts the overall weighted overall performance of all the algorithms.

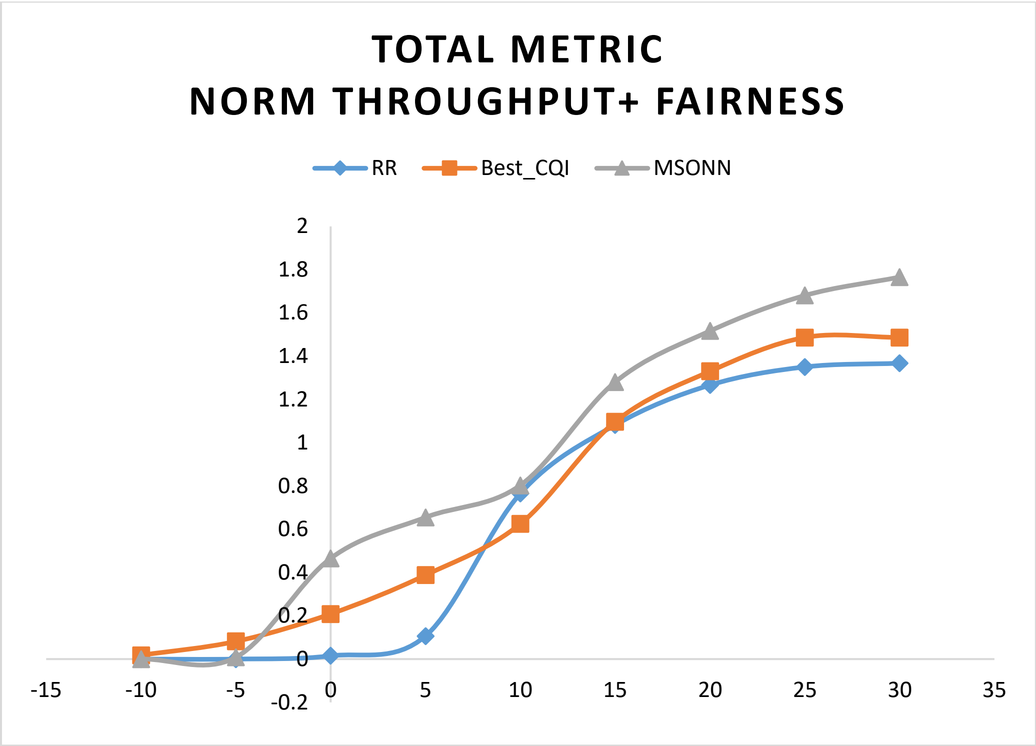

Figure 37 Combination (Fairness and Throughput) evaluation among different scheduler schemes.

It is clear the combination of the algorithms 1 and 2 make the downlink performance more reliable to the end user UE. The individual users have been provided higher throughput than the RR scheduler is providing. All this, with giving a low Bit Error Rate BER during the whole course of different environment.

It's clear from this previous figures the performance with Modified Self Organized scheduler is a way better in terms of fairness as we can see: The Block Error Rate of the cell, it's even more clear on the Block Error Rate on the individual Users UEs and it’s clear now the UEs almost have very close similarity in terms of UE throughput.

This kind of scheduling techniques (Modified Self Organizing Mapping) gives the promising optimization between providing the highest Cell throughput and fairness among users (UEs).

Chapter 4. Predictive Recurrent Neural Network techniques

We will discuss recent developments and enhancements of recurrent neural network structures with learning. The recurrent neural network is a dynamic system that has the ability to generate predictions of (the expected) values of a time-series with a relatively small margins of error.

In this chapter, we are going to apply the basic Recurrent Neural Network (bRNN) that has been introduced in [38] towards providing predicted values for the next time-series data given a history of received prior time-series data of a user's channel. These network will be tailored to predict the next Channel Quality Indicator (CQI) a user's channel over an duration of received readings. Hence, the bRNN will provide a prediction (of the mean of the channel CQI) for the next TTI interval.

4.1. Implementing Novel Recurrent Neural Networks Scheduler Algorithm

Recurrent Neural Networks (RNN) are using time series prediction toward making a model of Resource Block scheduling. This approach adopts an RNN, called Basic Recurrent Neural networks (bRNN), as introduced in [38]. The goal here is to use the prediction model based on the feedback received from the previous measurements profile by applying gradient decent in updating of the weights. This type of work toward enhancing LTE-A communication systems performance and making it reach the promise of 3GPP in Release 11. An advantage of using a bRNN network is that it is dynamic in tracking random changes as in our communication situation with wireless channel.

Based on [38], the main neural network equations are:

$$x(t+1) = A\,x(t) + U\,h(t) + W\,s(t) + b \tag{4.16}$$

$$h(t) = \sigma\,(x(t)) \tag{4.17}$$

$$y(t) = V\,h(t) + D\,s(t) + c \tag{4.18}$$

The matrix A is fixed with eigenvalues less than 1 in absolute value. However, the matrices U,W,V, D and the vectors, b and c, represent the weights and biases, respectively, that will be updated at each mini-batch or epoch. When successfully trained and adapted, the RNN learns to predict the profile pattern of the users' values of the Channel Quality Indicator (CQI). The vectors x(t) and x(t+1) are the present and future states, respectively, and h(t) is the hidden unit vector. The vector y(t) is the output of the RNN, which should become close to the target value after the RNN is successfully trained.

For constant (fixed) parameters, and assuming they are stable, these equations execute inference from input sequence to states to hidden units, and finally to outputs. The key challenge in RNNs is to execute training procedure to update the parameters (i.e., weights and biases) in order to realize a sequence to sequence mapping using training data. Towards that end, the backpropagation through time (BPTT) and its variants can be derived from constrained optimization and optimal control which produces a co-state (sensitivity) dynamics known as backpropagation and often denoted by delta or lambda variable [38, 39].

The main factor of the updating procedure is the variable Lambda [39]. The updating procedure of the weights is a supervised version, as the Back Propagation through Time (BPTT) technique, which is the gradient descent of the weights. The gradient descent developing process is conducted through BPTT [116].

4.1.1. The adaptive algorithm:

As the equations (4.16) to (4.18) are the recurrent neural network system, the weights matrices and its factors have to be fixed in the testing period. We reach to this fixed weights by training theses set of weights with train of possible input to this network while updating these weights through this training period. Through this training the matrices weights A, U, W, V and D as well as the biases b and c are changing/updating at each iteration. This means only through the training the set of weights will be changing with time. All the equations have been provided in depth and details in [38]. In this work we consider (t) as the discrete index of the training iterations. Based on the analysis that has been provided in [38] and [39], we can explain the updating procedure of the weights matrices based in the co-state $\lambda(t)$. we can calculate the co-state as:

$$\lambda(t).= (A + U\,\sigma'(t))^T \lambda(t+1) + (\sigma'(t))^T V^T e(t) + \beta_1 (\delta L(t)/\delta x(t)) + \beta_2 (\delta L(t)/\delta h(t)) \qquad (4.19)$$

Equation (4.19) is being updated at each iteration of training our network as $0 < t \leq N-1$. The co-state is the main factor of updating all the weights. The updating equations of every weight matrix can be expressed as:

$$\Delta U(t) = -\,\eta\,\lambda(t+1)\,(h(t))^T \qquad (4.20)$$

$$\Delta W(t) = -\,\eta\,\lambda(t+1)\,(s(t))^T \qquad (4.21)$$

$$\Delta b(t) = - \eta\ \lambda(t+1) \qquad (4.22)$$

$$\Delta V(t) = - \eta\ e(t)\ (h(t))^T \qquad (4.23)$$

$$\Delta D(t) = - \eta\ e(t)\ (s(t))^T \qquad (4.24)$$

$$\Delta c(t) = - \eta\ e(t) \qquad (4.25)$$

We consider e(t) as the error between the observer and the desired output in the training process. The parameter η is the learning rate process. All these previous updating equations are applied by each iteration in the training period of the neural network.

$$e\ (t) = yh(t) - y(t) \qquad (4.26)$$

It is clear y(t) in previous equations points to the correct target value of output at time t, and yh(t) represents our calculated output at the same time t, while y(t) represents the next TTI target during training. In the training phase, the adaptive algorithm seeks to update the bRNN parameters, e.g., U,V and W, in order to minimize the error function and renders (the mean) yh(t) become close to the mean target y(t). Figure 34 shows the unfolding of the RNN over a fine time duration for an illustration time-stepping sequencing of input to (internal) state to corresponding output of a generic RNN.

$$xh(t+1) = Ah\ x(t) + Uh\ h(t) + Wh\ s(t) + bh \qquad (4.27)$$

$$h(t) = \sigma\ (x(t)) \qquad (4.28)$$

$$yh(t) = Vh\ h(t) + Dh\ s(t) + ch \qquad (4.29)$$

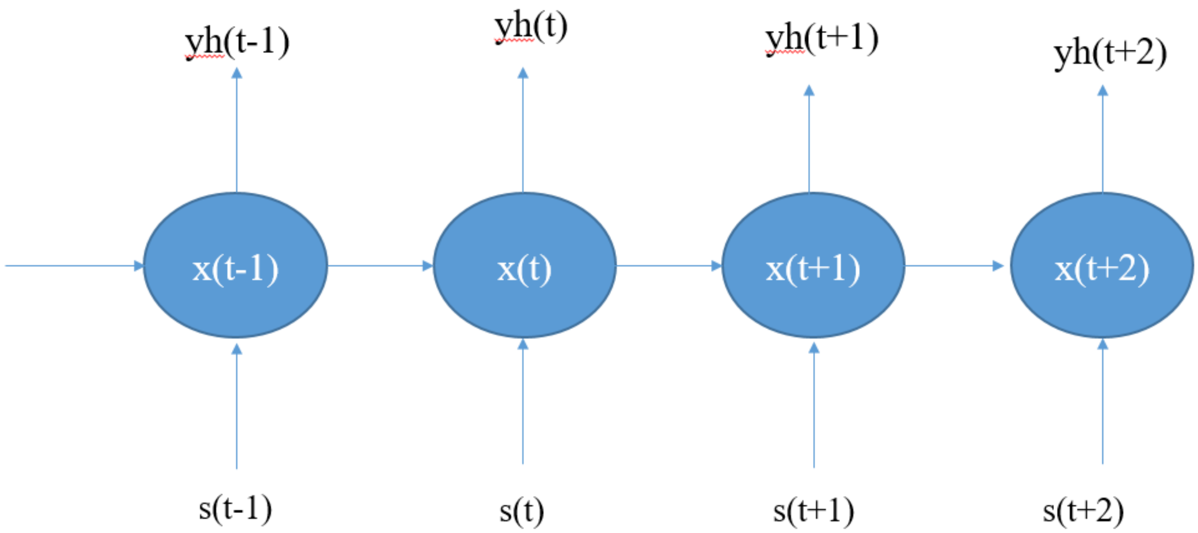

Figure 38 Recurrent Neural Network RNN unfolding over time index

Equations (4.16), (4.17) and (4.18) process are summarized in the diagram shown by figure 38. x(t) is the state vector , s(t) is our input data vector and yh(t) is the output vector.

4.1.2. Evaluation of the Basic Recurrent Neural Network (bRNN) prediction:

The evaluation of the bRNN prediction uses the codes developed in [39] and will be adapted here toward random values with means representing the expected values of the Channel Quality Indicators CQI feedbacks. The input data will be provided to the weights in just regular dynamic bRNN system by using regular equations (4.16),(4.17) and (4,18) for such number of mini-batches or epochs. Then, after successful training, we will perform inference using the resulting bRNN for prediction. Sample performance results are shown below for one-dimensional state, with a scalar and output variables. The displayed results also show the co-state variable (Lambda) which represent the back-propagating error at the end of training [39]. It is noted that variable Lambda has zero mean over the horizon (duration) which in turn indicates that state and output tracking has been successful:

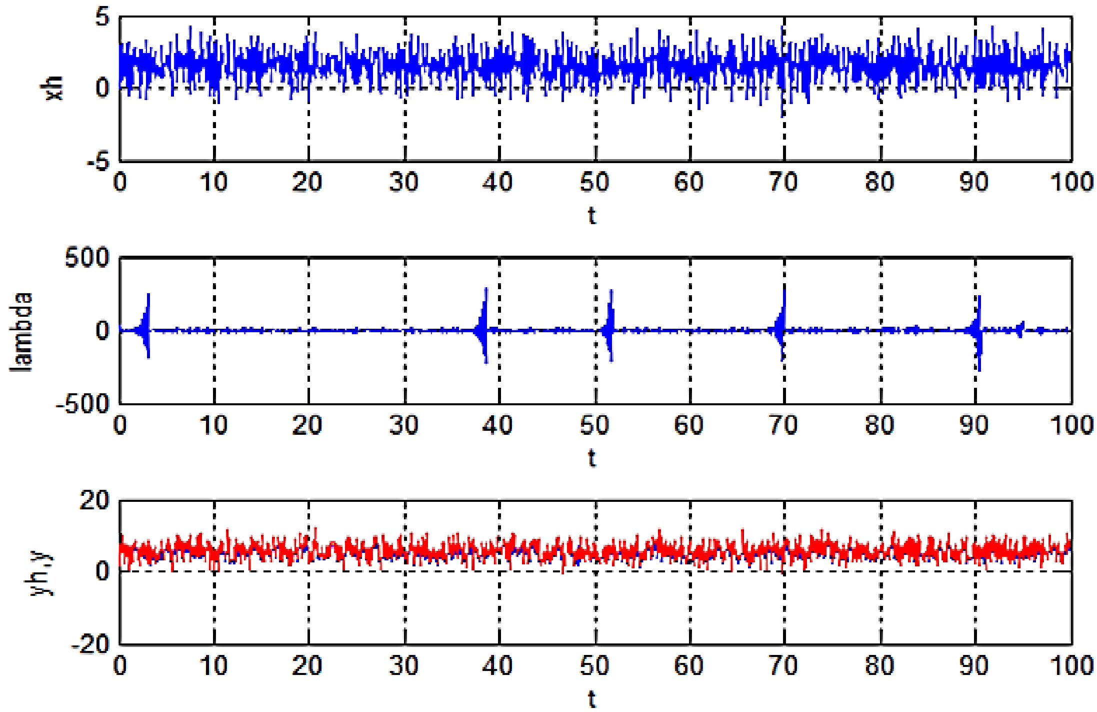

Figure 39 Simulation depicting an example results of the training process of bRNN

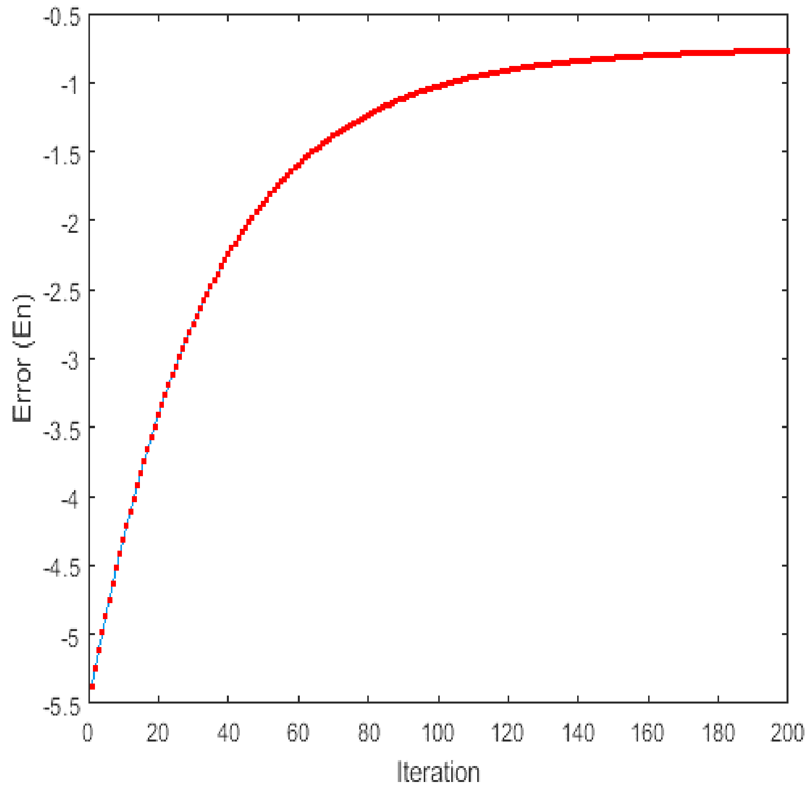

Figure 40 An Example output error signal profile during training

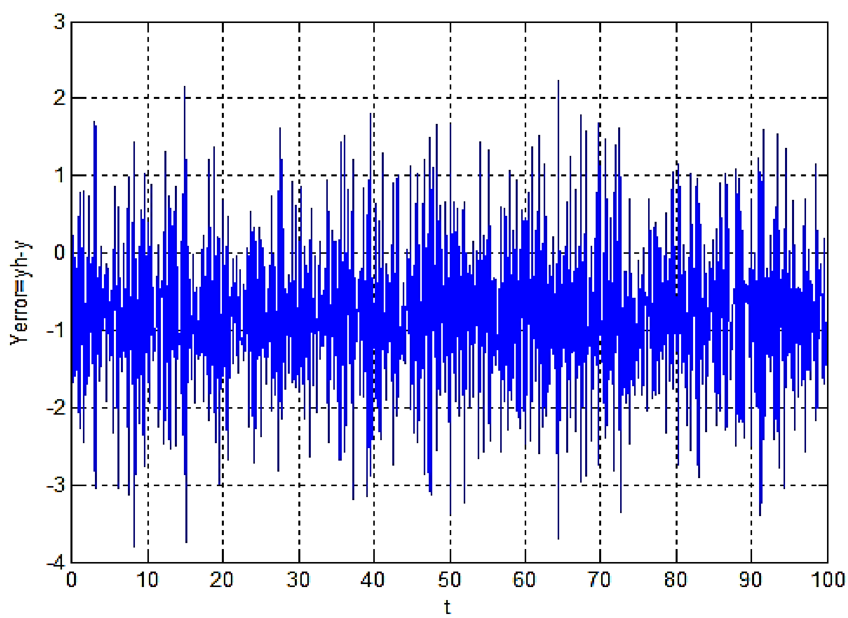

Figure 41 Example Output Error profile

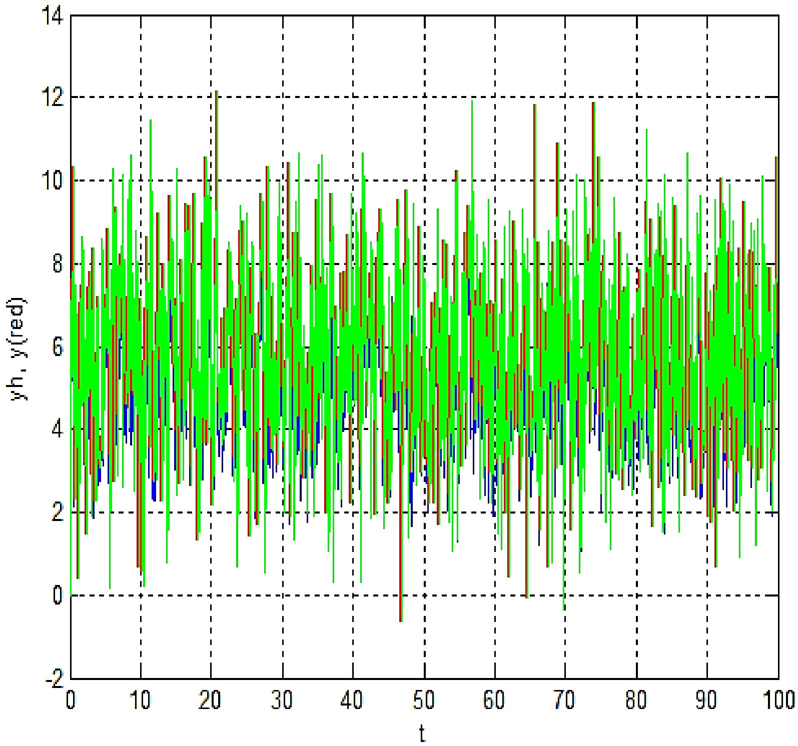

Figure 42 Dynamic system output and target values

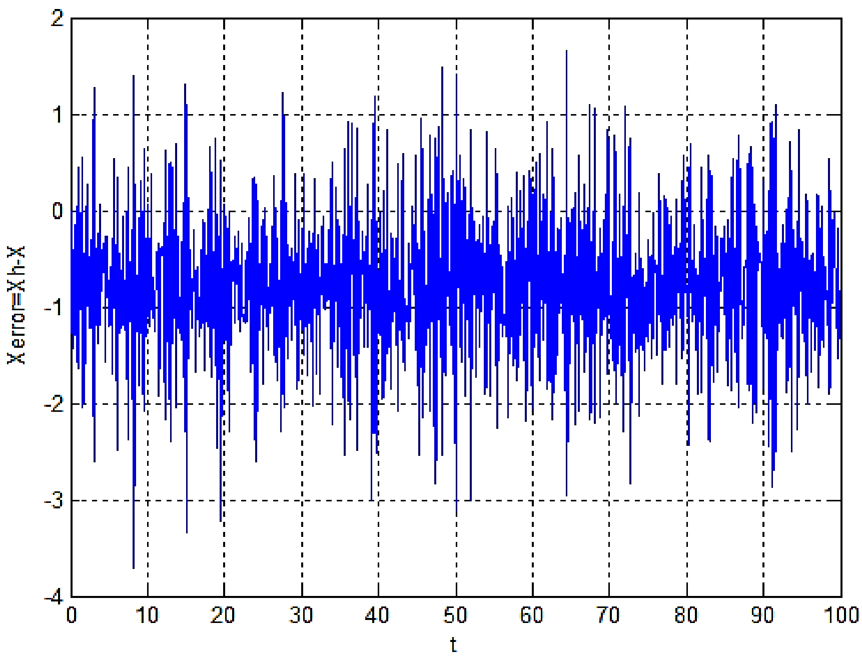

Figure 43 Example State Error

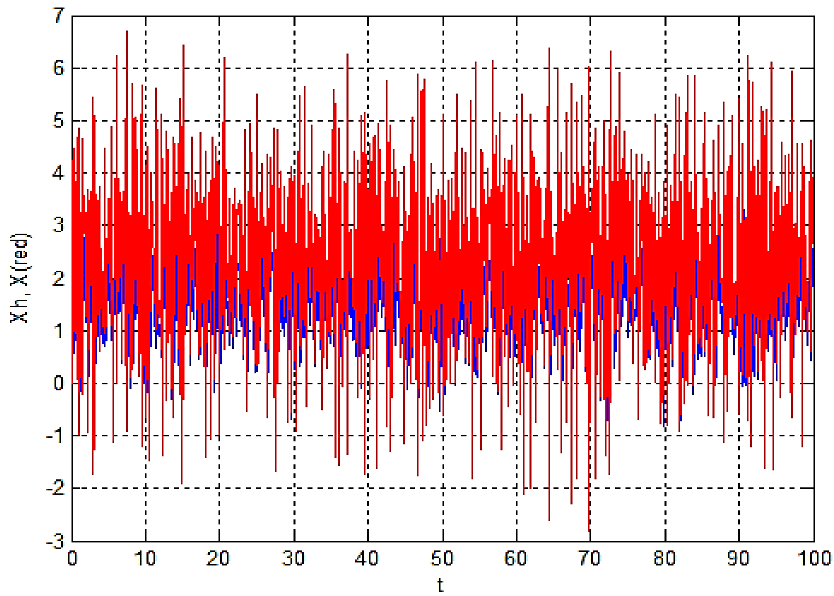

Figure 44 Example State performance

The predictions has been provided. As we are at time t, we have the real target value of y(t+1), and thus the predictor output yh(t) will be estimating the target value y(t+1). The previous plots show the good performance of the future prediction form of the bRNN dynamic system. Zooming the plot of the output performance of the system, the target values and the shifted version of the target output are shown in figure 41.

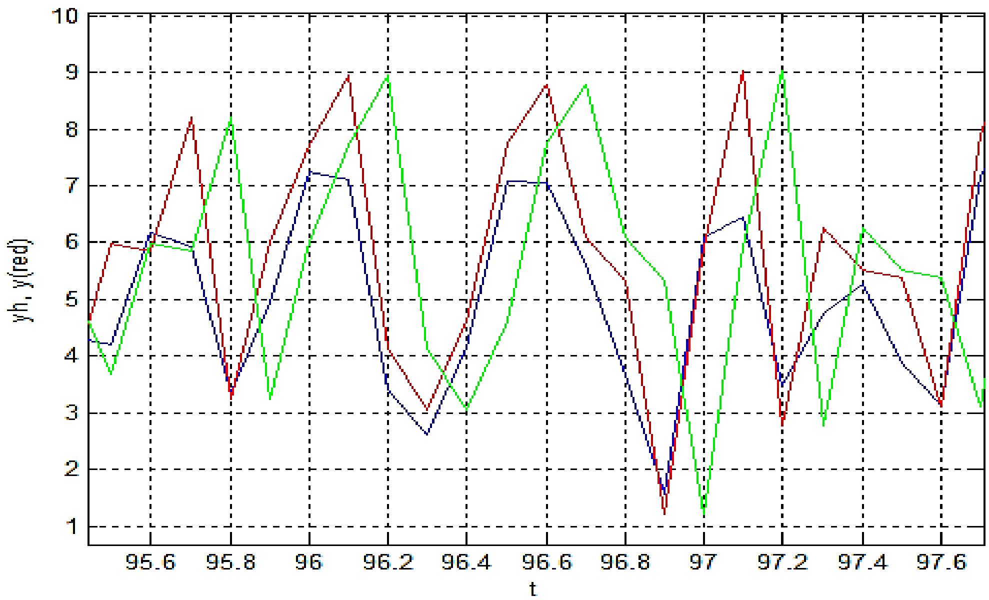

Figure 45 Output performance

The dynamic bRNN output is represented by the blue line, and it is performing exceedingly well in regards to the real targeted value, as represented by the red line (which is a one-step shift of the target shown in green). The output of the network reasonably tracks the one-step value of the target.

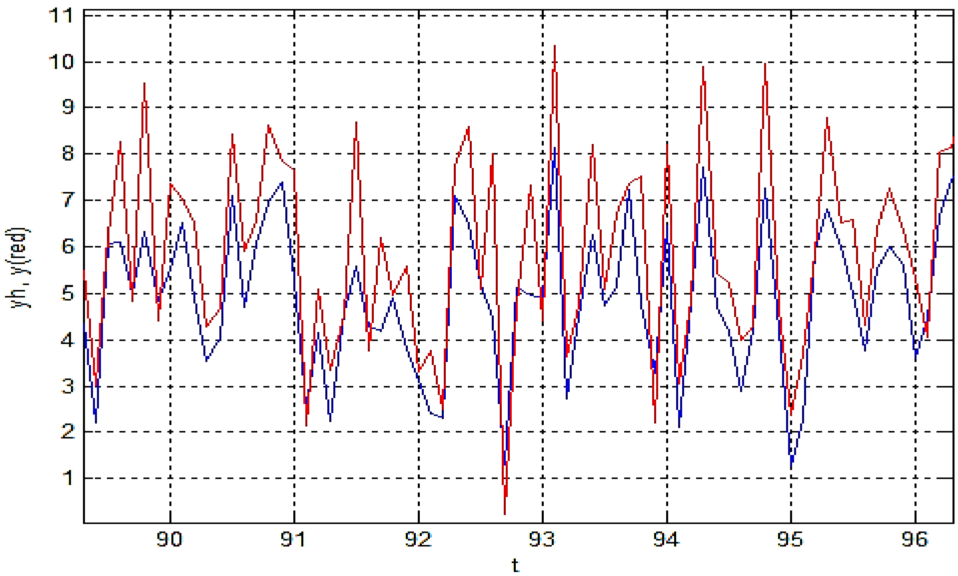

Figure 46 Predicted values vs Real values

We are observing reasonable tracking in the two sample previous plots. These results show after the weights converged the dynamic bRNN and provide great prediction readings.

Chapter 5. Novel Scheduler to LTE Resource Blocks by applying Recurrent Neural Network techniques

The implementation of a RNN algorithms into the LTE Resource Blocks (RB) scheduler can be explained in systematic steps. These clear steps summarize our technique in employing a RNN algorithm into a scheduling procedure. The RNN scheduling algorithm constitutes several computational steps. The comprehensive view for the algorithm is as follows:

As the input space of activation patterns are generated in accordance with a certain probability distribution. The dynamic system that bRNN provide will learn the pattern of the channel performance of the users that attached with e node Base. In this work here we apply the whole process of learning and testing procedures at every transmission action. Where in the first part of the TTI we are training the bRNN and testing it to provide results to the scheduler. Then, we are just providing the test part of the procedure only. This over all procedure applied every TTI.

Because the main feature of the RNN is the storage unit (hidden State), which provide memory to the bRNN about the input data. As well as our work here in wireless mobile system which include mobility to the action this lead to high probability of changing environment in short period. So, It is better to repeat the whole process (Training and Testing) every TTI.

5.1 LTE-A Resource Blocks With Recurrent Neural Network Techniques

In this chapter, we apply the bRNN procedure that was outlined in chapter 4 to provide predictions of the Channel Quality Indicators CQI for the next TTI period. After initial training, one can employ the bRNN for inference or prediction. In that scenario, the bRNN predicts the

CQI of the channels among users based on the last previous profile reading. As the CQI is predicted before TTI period, one can optimally schedule or prioritize the users Resource Blocks based on chosen criteria.

In general, we can summarize the bRNN algorithm as:

1) Initialize weights of the observer: this can be done by choosing random values for the initial weight vectors Uh, Wh, Vh and Dh as well as initiate the constants bh and ch to zeros at equations (4.16), (4.17) and (4.18). This will happen with initializing current only matric values for the state values x(t). Then, when the algorithm is ready to work, it will adapt itself as t=1,2,3…,l. The dimension of state x(t) is changeable as it does not have to be the same size of the input data, we chose to make it 1

   It is may be desirable to initiate the magnitude of the weights with small values. Other parameters such bias and matric bh and ch in equations (4.16), (4.17) and (4.18) needed to be initialized. This initialization has a counter and it is only executed for the 1st transmission action only. The matric Ah will be constant through the whole process Ah = α I.

2) We run bRNN algorithm every transmission action. CQI of the previous transition matric will be provided and set as our input s(t) = CQI(t). at each TTI we are applying s(t) as our input data and the reference/desired value y(t) = s(t+1) = CQI(t+1)toward training our bRNN network in the training phase.

3) We compute the error between the CQI feedback and the observer E(t) = yh(t) – y(t). This E(t) is evaluator of our predictions and it will be used toward updating the weights through the training phase. We can use E(t) as alert toward starting the training phase if E(t) exceed threshold values.

4) We run the set of equations (4.16) to (4.18) to get yh(t) and xh(t+1) at each TTI.
5) We apply the gradient decent calculations [38] toward use it into updating the observer weights for the next transmission action. This step has a counter and it will be executed only for the first 200 transmission action, It is called training phase.
6) We will apply the output of this algorithm which is the vector yh(t+1) the prediction of the next CQI feed back.

Weights of the observer are updated by set of equations (5.22).

$$xh(t+1) = A\ x(t) + Uh\ h(t) + Wh\ s(t) + bh$$

$$h(t) = \sigma(\ xh(t)) \qquad (5.22)$$

$$yh(t) = Vh\ h(t) + Dh\ s(t) + ch$$

Applying equation (5.22) only without applying updates to the weights will be to the rest set of TTI If there are no alert from E(t).

In equation (5.22) σ(t) is the nonlinear function and it is considered as the learning–rate parameters, and σ(t) or h(t) are varied dynamically during learning for the best result.

There are steps will be executed for the one iteration and they are for initialization, other selected steps will be executed for the first 200 transmission action , they are for seeking of training our algorithm and we consider this as warming up period. The time line of this algorithm can be divided to two stages as shown in algorithm 4. Training stage: where all the weights (General output plant & Optimal observer) are implemented and applied. Then, Execution stage: where we execute only the observer part).

This is Algorithm 4:

Algorithm 4: bRNN updating Algorithm

1:**Procedure** INITIALIZATION

2: Ah ← Set this matric as constant Ah = α I

3: Uh,Wh,Vh,Dh ← Initializing the adaptive set of weights

5: bh,ch← Initializing the adaptive set of biases

6: α,β,η,ϛ← choosing optimal observer parameters

7: s(t) ← Fetch the vector of indictors for the first transmission action

8:epoch ← set number of epochs

9: Training Phase: For the first 200 transmission actions

11: calculate xh and yh ← applying optimal observer:

xh(t+1) = Ahx(t) + Uh(t) + Wh s(t) + bh

h(t) = tanh (gamma xh(t))

yh(t) = Vh h(t) + Dh s(t) + ch

12: bRNN error function evaluation

E(t) = CQI - Yh

13: calculate gradient descent (BPTT) to all bRNN weights coefficients

---

Algorithm 4 (cont'd)

14: update all bRNN weights

15:Processing the loop: From transmission action =201 to end

16: calculate xh and yh ← applying optimal observer:

xh(t+1) = Ahx(t) + Uh(t) + Wh s(t) + bh

h(t) = tanh (gamma xh(t))

yh(t) = Vh h(t) + Dh s(t) + ch

17: Provide the prediction

18: Close

Algorithm 4 will be called at each TTI = 10ms by algorithm 5 as it is responsible of the management and clustering of the Channel Quality Indicator CQI feedback. In the previous algorithm.4 the CQI feedback of the previous TTI has been fed to the algorithm as x(t). then we run the bRNN algorithm with time shifting explained in chapter 4 to provide the prediction of the values of CQI of the current TTI before the E node B receives it. Based on these predictions. We will map and position the users to the Resource Blocks RBs for the coming TTI. More details about the procedure will be provided in the next sections

5.2.1. The Scheduler Algorithm Framework By Implementing the bRNN In Scheduling:

As bRNN is supervised learning that has prediction to the future state possibility feature, we are applying this feature toward providing us with prediction for the future expected state based on the previous performance, and then it will be updated based on the real values. The input data s(t) will be the Channel Quality Indicator (CQI) of the last feed-back from the previous signal we received from the users UEs. The code will run for one step size at each TTI. So, the first 4 to 5 TTIs will be as considered as a training period for the algorithm. Then, it could start providing us with wise decisions for the user's channel pattern. So then we are worming up our system with the first 200 TTI after that our bRNN algorithm become solid and ready for the practice.

Algorithm 5: Self Organizing Scheduler

1:**Procedure** FETCHING

2: Find the UE feedback of the previous transmission action

3: CQI ← Build the UE matrix of the previous transmission action

4:Itr ← Assign Number of Iteration

5:THD: Eliminate UE with CQI below the threshold

6: ƒ(x) = SoftMax(x) ← Final Shape of the non-linear function

7:Processing the loop

8: SGN ← Assign the group needed to be mapped

9:Call ***bRNN*** Algorithm for execution

11:Wait transmission action to be finish, no schedule permitted…..

12: @ End of transmission action, Release the scheduling map

13: Close

It is clear Algorthim4 is showing the superposition method of the user mapping into the Resource Blocks RBs procedure. By applying Recurrent Neural Network based algorithm toward mapping the Resource Block RB, this will provide a prediction for the Channel Quality Indicator CQI feedback. This means that RNN can build state over the entire training sequence and even maintain that state if needed to make the prediction.

5.2.3. Mapping the bRNN scheduler by SoftMax:

This section contains the details of step number 3 on the **scheduler Algorithm framework bRNN**; this step has a new motivative way of mapping which provide stability and accelerate the process of scheduling, all this has been provided based on the bRNN prediction. This has been done by using non-linear function the SoftMax function. This step really makes the scheduling process faster and made a hierarchy in the scheduling process, which helps toward managing the users into the resource blocks RB grid. This matters significantly when the cell dealing with large number of users. It receives the predicted users feedback CQI and map them to the resource blocks.

1- Fetch the predicted users feedback (CQI) of the users and name all of them
2- Provide SoftMax non-linear function to each user. So, each user will have class accordingly
3- Map the clusters proportionally based on its SoftMax value to the Resource Blocks RB grid

$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \quad \text{for } j = 1, \ldots, K.$$

So, by choosing the users and then ranking the clusters, they will be probabilistic based not just a signed value criterion, this provides us with more robustness and adaptability to the pattern.

4- Distribute the users in each class equally to the RBs portion of their class to provide kind of fairness

5- Print the map of this transmission time.

The process in step 3 at algorthim5 could be summarized to:

Algorithm 6: bRNN Scheduler Algorithm Mapping

1: **Procedure** FETCHING

2: UE prediction $\leftarrow$ Group CQI feedbacks by Algorithm 4(priorities by bRNN)

3: SoftMax $\leftarrow$ Each user highlighter by non-linear fun

4: **Procedure** Processing the loop

5: Mapping the Cluster proportionally with SoftMax value

6: SGN $\leftarrow$ Assign the UE needed to be mapped

7: DST $\leftarrow$ Distribute UEs in same Cluster equally

8: Classes $\leftarrow$ Build the UE matrix of the previous transmission time

9: Wait transmission time to be finish, no schedule permitted…..

12: @ End of transmission time, Release the scheduling map to step4 in Algorthim5

13: Close

In this algorithm, we provide proportional fairness of scheduling. As provided by step number 4. The users in the same CQI prediction have been provided the same number of resource blocks. This happens with maintain providing the priority to the users with the high CQI and higher number of RB.

5.2.4. bRNN Scheduler Algorithm Performance

The figures below describe the great performance of this bRNN scheduling algorithm: the performance evaluation parameters are E node base throughput, Bit Error Rate BER of the E node B, throughput of randomly selected Users Equipment UE and the UE Error bet Rat BER versus several Signal to Noise ratio SNR environments. The next 6 plots explain the performance criteria:

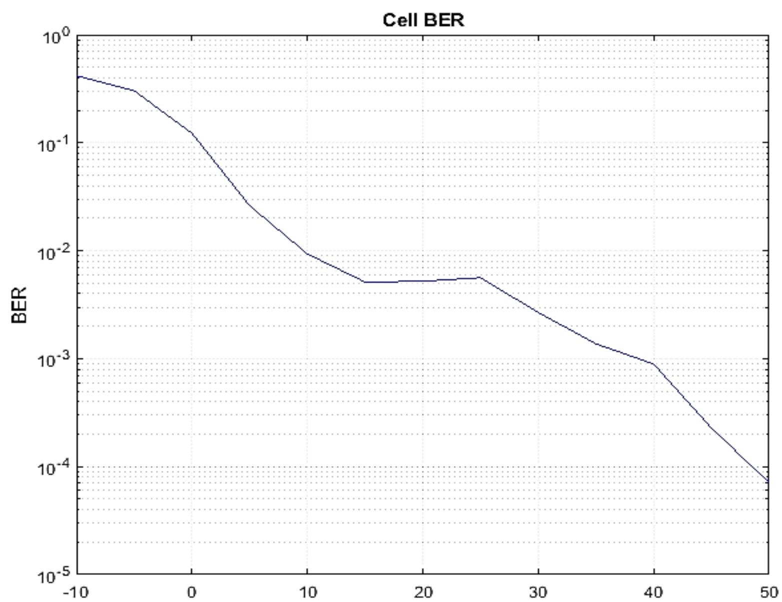

Figure 47 Block Error Rate for the Cell using bRNN

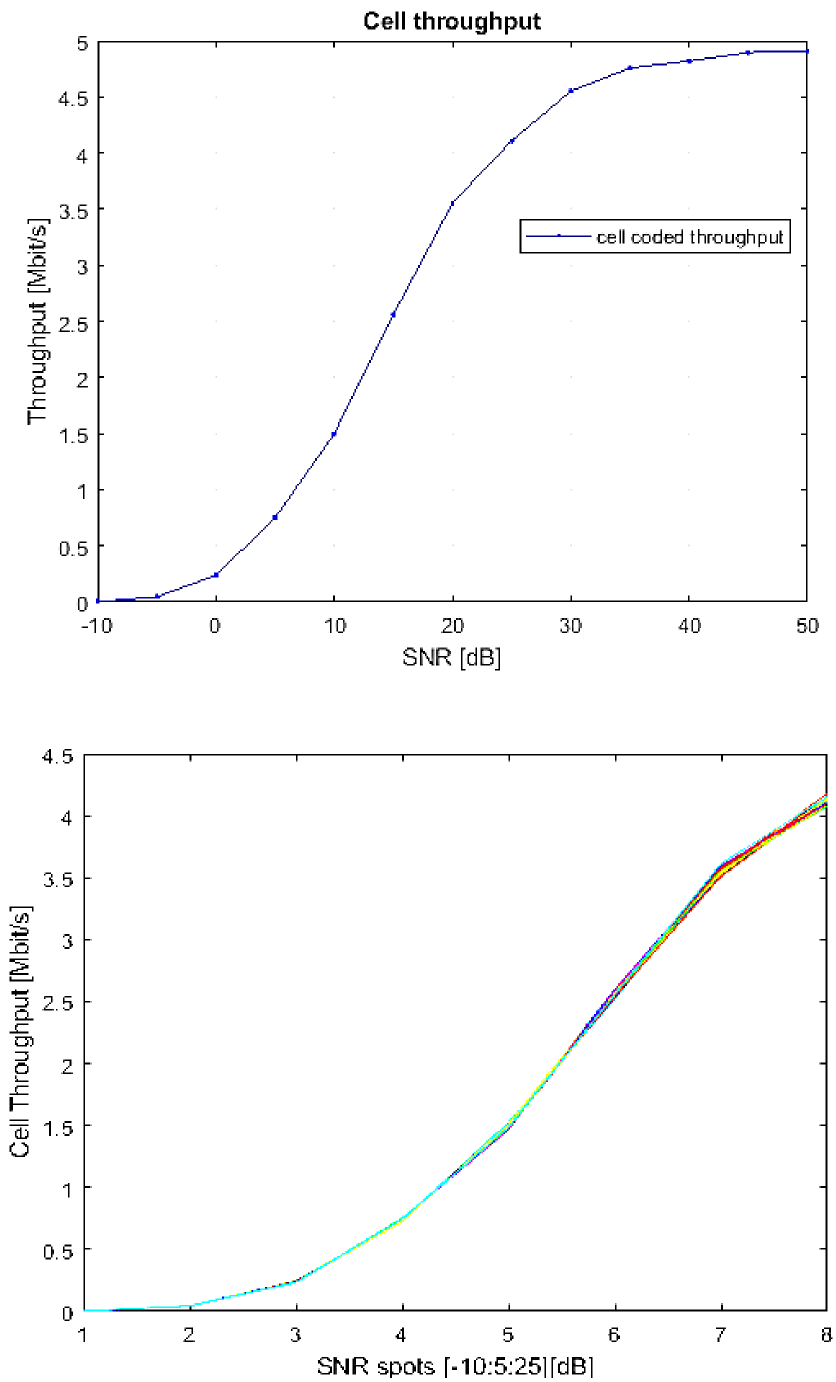

Figure 48 Throughput for the cell using bRNN

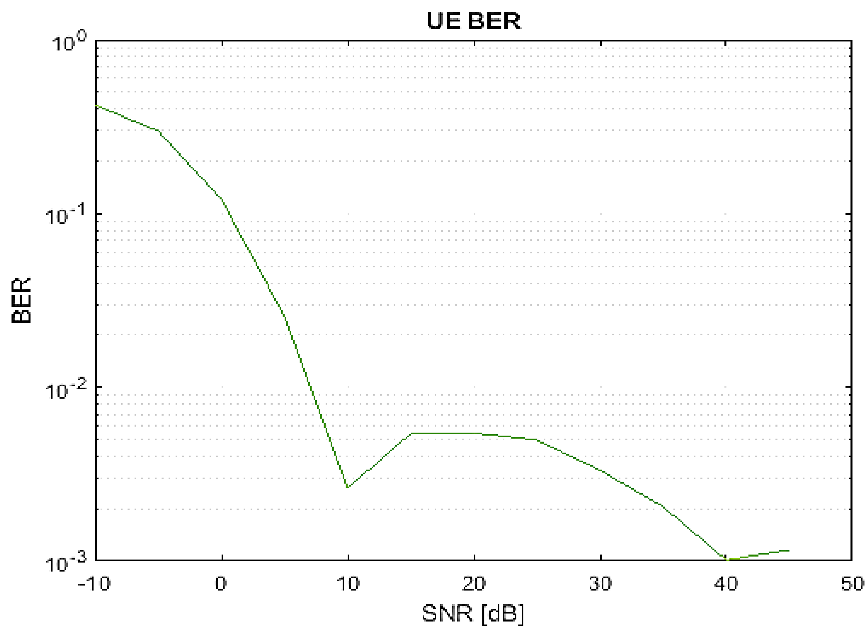

Figure 49 Block Error Rate for User 3. bRNN

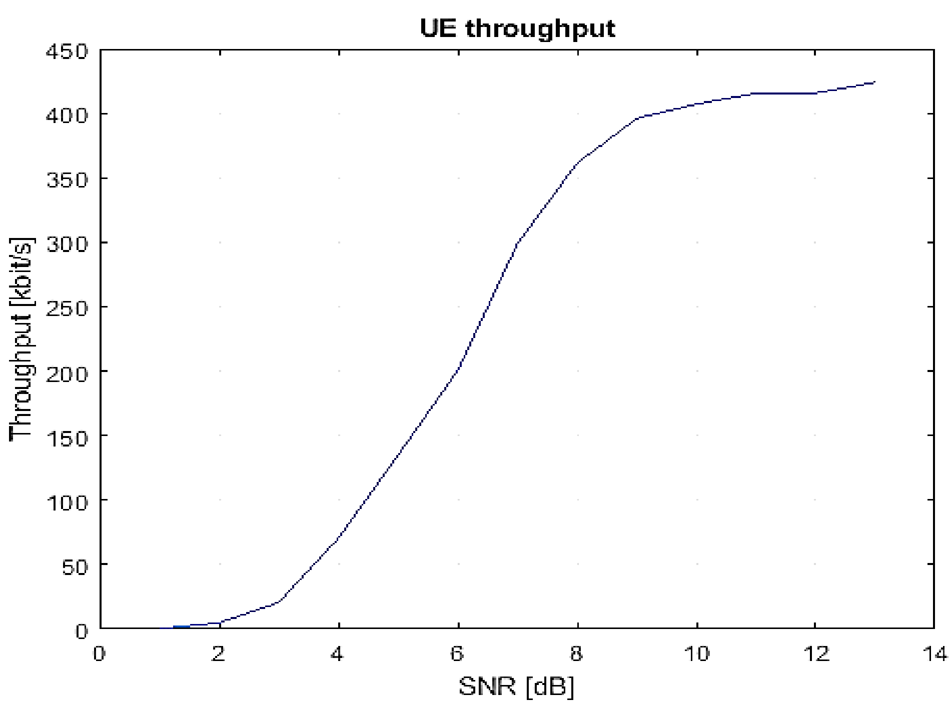

Figure 50 Throughput for User 3 bRNN

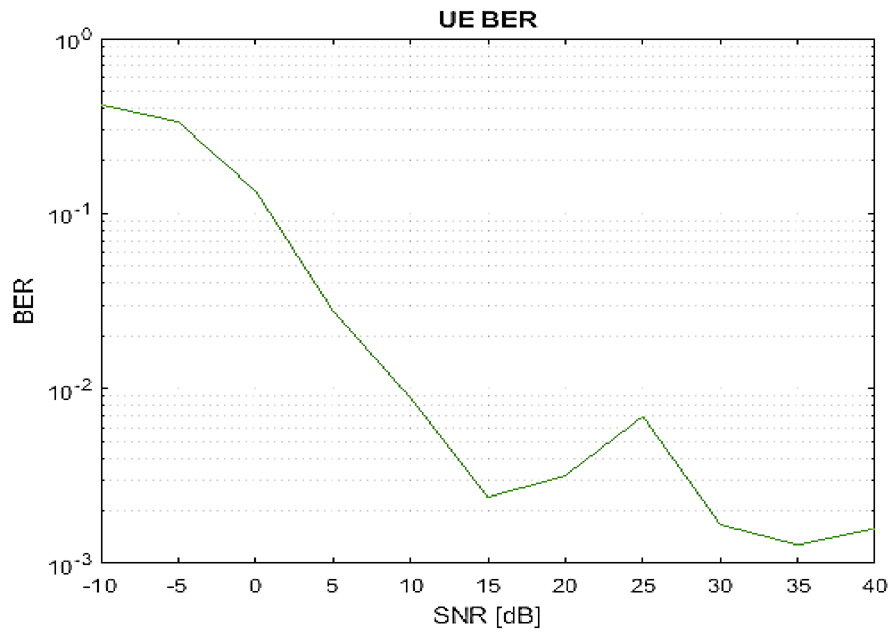

Figure 51 Block Error Rate for User 10 bRNN

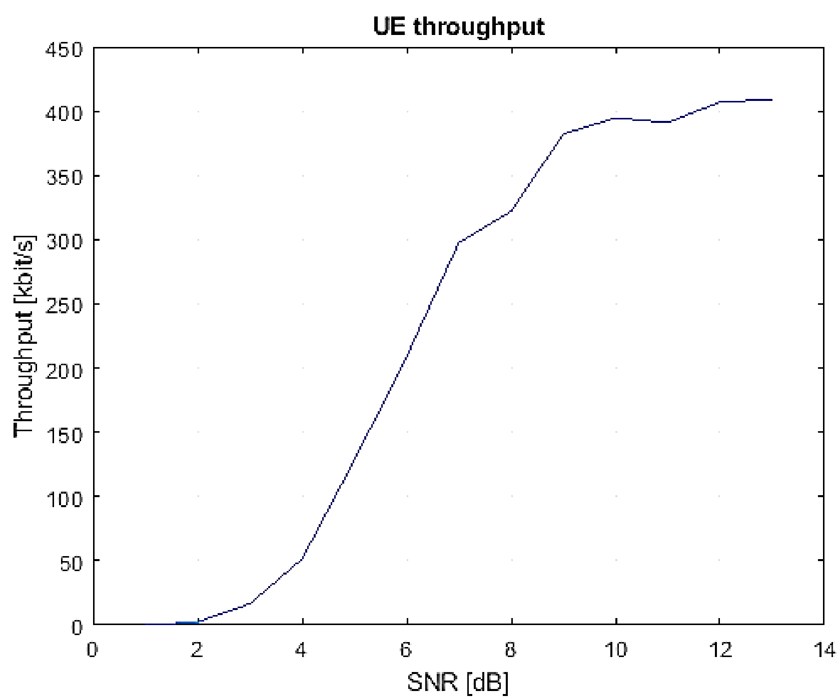

Figure 52 Throughput for User 10 bRNN

Figures starting from Figure (43) to Figure (48) show the performance of the system using the Novel modified-RNN scheduler algorithm. The performance shown in Bit Error Rate and Cell throughput that shown at these plots it is observable the system is providing dynamic reliability in the individual users point of view. As there are no sharp edges in the curve showing in the cell curves and it has become more clear in the individual users plots, like User 10 and User 3. That they have high smooth curves over all the period.

It's clear from these previous figures the performance with Modified Recurrent Neural Network scheduler is much better in terms of fairness as demonstrated by: The Block Error Rate of the cell. It is even more clear on the Block Error Rate on the individual users UEs and it's clear now the UEs almost have very close similarity in terms of UE throughput.

This kind of scheduling techniques (Modified Recurrent Neural Network) gives promising optimization between providing the highest cell throughput and gives fairness between users UEs. This is real Proportional Fair scheduler.

All these results have been provided with complete set of random process among all characteristic of the procedure. As the matlab box provide us with random set of all sub files such is the channel modeling and environment sets, we provided this process with complete different scenarios as figure 48 proof, so we end up with solid results in the same sequence such as in figure 53, to figure 55.

We have compared the performance of bRNN algorithm verses (SONN and the well-known existing benchmark algorithms, namely, the Round Robin (RR) and the CQI-max algorithms), on the cell throughput criteria. Figure53 depicts the resulting the cell throughput versus SNR for all four different scheduling schemes.

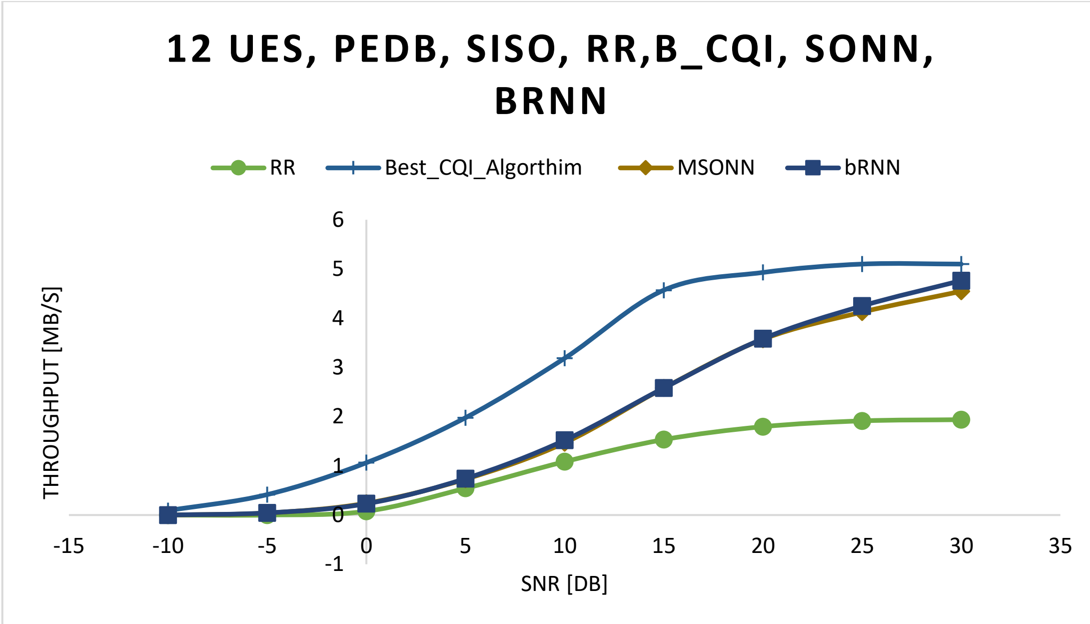

Figure 53 Cell throughput for the four different scheduler schemes.

It is noticeable that the RR scheduling performance is the worst in throughput, since it does not consider the user channel condition into account. The CQI_max scheduling achieves the highest overall throughput in the example, but at the expense of notion of "fairness" to all users. As depicted in Figure55, the new bRNN algorithm is the providing a trade-off between the throughput and a notion of fairness to all users. In this particular example bRNN algorithm provide better trade-off than SONN. As in figure54 its throughput performance is in the average scope. After normalizing the throughput performance among all different types of schedulers, we got the matric of figure 55. This matric will be applied for overall performance.

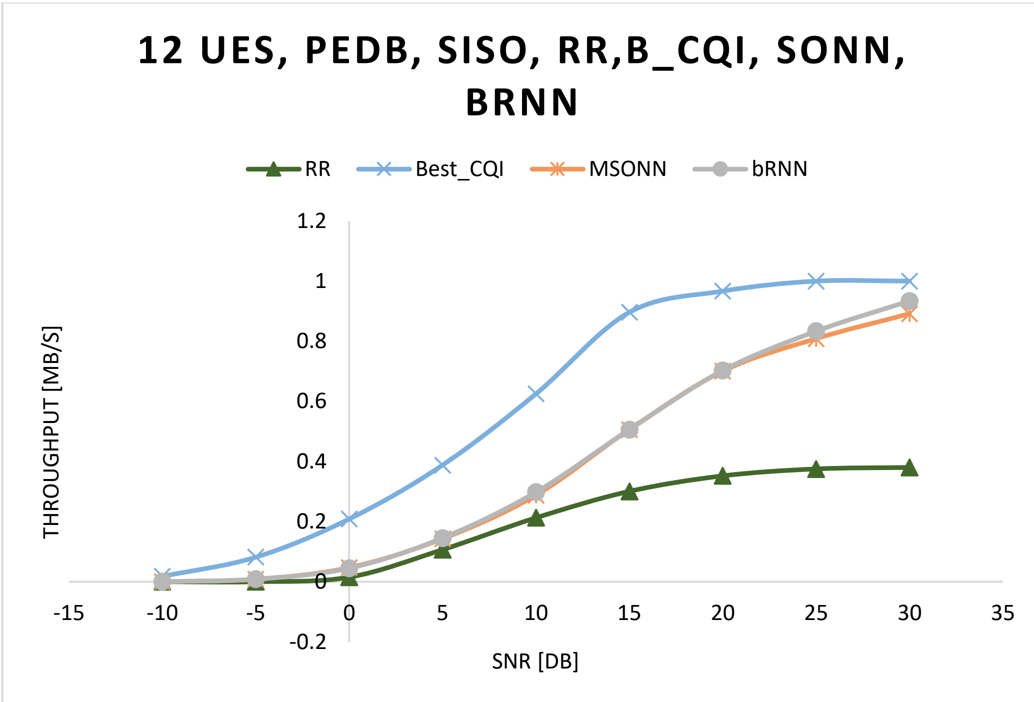

Figure 54 Normalized cell throughput for the four different scheduler schemes.

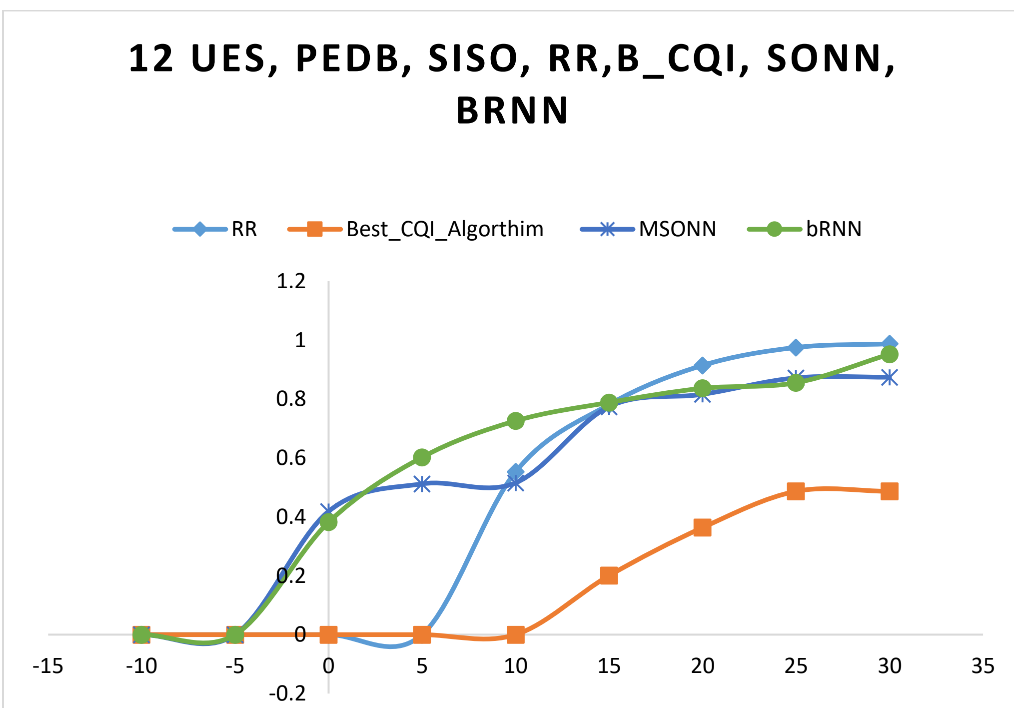

Figure 55 Fairness among users for the four different scheduler schemes

Toward a full comparison of all algorithms performance, we end up with matrix that represents the normalized sum of throughput matrices and fairness matrices in the evaluations. Figure56 depicts the overall weighted overall performance of all the algorithms.

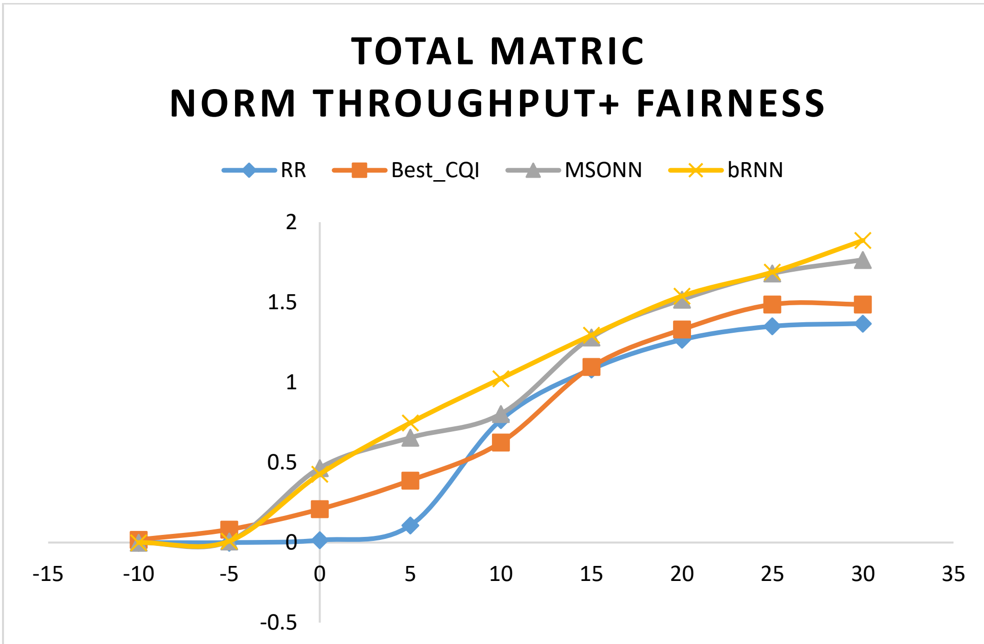

Figure 56 Combination (Fairness and Throughput) evaluation among different scheduler schemes.

It is clear that the combination of the algorithms 4 and 5 makes the downlink performance more reliable to the end user UE. The individual users have been provided higher throughput than the RR scheduler is providing. All this, with giving a low Bit Error Rate BER.

Toward showing the difference performance of bRNN scheduler over RR scheduler in terms of throughput and fairness full comparison of all algorithms performance, we end up with matrix that represents the normalized sum of throughput matrices and fairness matrices in the evaluations. Figure 57 depicts the overall weighted overall performance of all the algorithms.

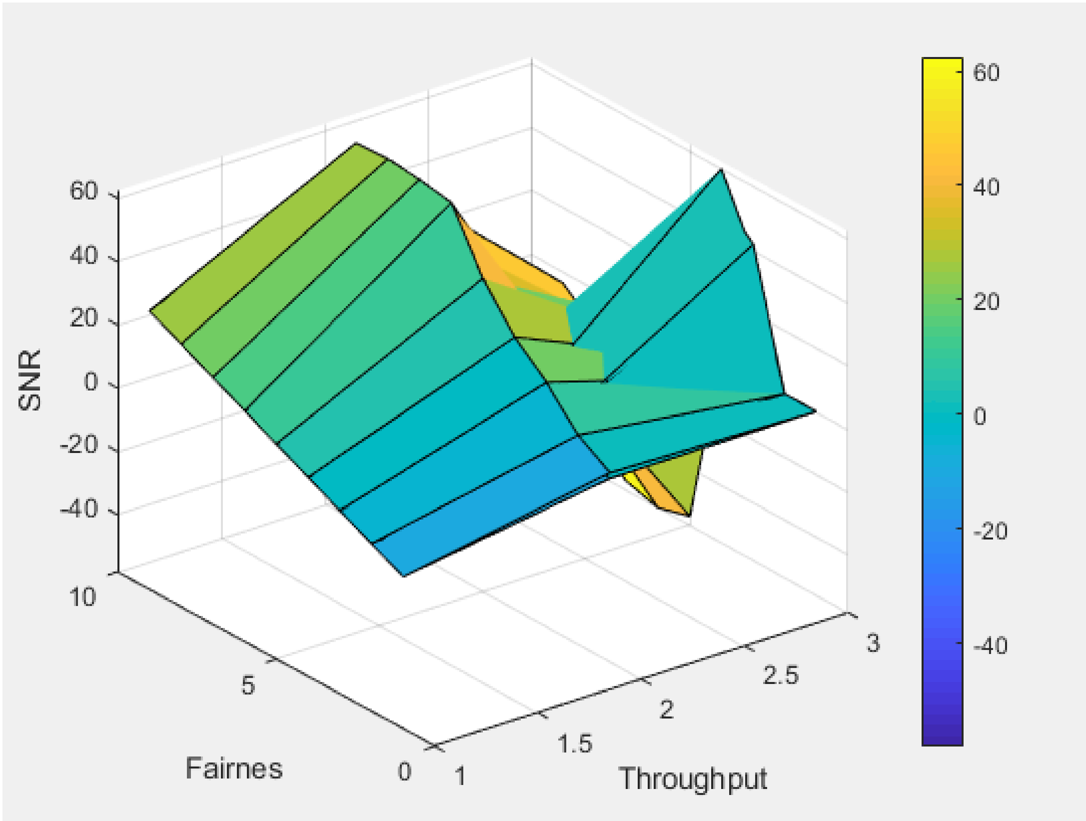

Figure 57 (Fairness and Throughput) evaluation of bRNN scheduler schemes comparison

It is observable from these figures the performance with bRNN scheduler is way better in terms of fairness: The Block Error Rate of the cell performing the best among other scheduler. It is even clearer on the Block Error Rate on the individual users UEs scale, and the UEs almost have very close similarity in terms of UE throughput performance.

This type of scheduling techniques give the promising optimization between providing the highest Cell throughput and give fairness among UEs. This is type of schedule can be considered as real proportional fair scheduler.

Chapter 6. Conclusion and Future Work

6.1. Conclusion:

- Self-Organizing promises in wireless cellular communication networks have been reviewed in the previous publications. In this work, a categorization of the previous projects have been done from presenting a deep understanding of what these new functionalities of future networks are, and such important results achieved thus far have been pointed out.
  The principle tenets of utilizing SO algorithms in remote innovation have been allocated. Although a careful analysis shows that some solutions in the literature are classic adaptive algorithms, others possess necessary features (scalability, stability and agility) required in any SO solution. Both classification and a characterization framework have been presented for SO and used to discuss the state of the art literature with simple classifications of self-configuration, self-optimization, and self-healing.
- Toward introducing a novel scheduling algorithm to improve the cell performance in LTE and LTE-A, Vienna LTE-A Downlink System-Level Simulator [37] has been operated to evaluate the performance of three already known and published algorithms Round Robin RR, Weighted Round Robin WRR and Max_C/I, then explore two novel scheduling algorithms that are introduced in this work with this Matlab toolbox. The performance has been evaluated through a spectrum of Signal to Noise Ratio SNR
- This work elaborated on the downlink packet-scheduling framework in LTE presenting. Then, a novel Self-Organizing Neural Network (SONN) scheduling algorithm was provided, and compared in performance to the famous Round Robin RR scheduler and Max C/I algorithm. The Max C/I algorithm was not reliable on maintaining the QoS that LTE-A promises to provide since

it could provide the users with bad channel conditions to “starve” resources, and could even assign all available resources to only one user in one sub-frame. But, despite the gains in accuracy, the SONN proposed algorithms are more complicated than the Max C/I algorithm. However, because they introduce compromise between fairness regarding resource distribution and prioritize the UEs, we propose they are the best channel to improve overall network performance. The simulation results prove that the proposed novel algorithms improve the overall cell throughput, both for PedB and VehB channel models (extensive simulation results for scenarios with 6,8 and 10 users have similar results and confirm the presented conclusions). With providing this SONN algorithm, fair balancing of the resources in the cell is grantee. The SONN scheduling mechanisms prevents that no user in the system is degraded or starved by supporter routine in the algorithm. The future developments could include a QoS metrics when making the scheduling decisions.

- Within this thesis, a new approach of applying the Recurrent Neural Network has been introduced and applied toward provide predictions. The dynamic system that RNN provides in some algorithms leads to following the pattern of the output performance because of the hidden unit in the RNN, all these enable the full algorithm we apply in this system to give accurate prediction values. Here we experiment with the base Recurrent Neural Network RNN to predict by training the weights to warm up and then run by applying random values over the entire time. Output performance, state performance and error measurements evaluated the performance with evaluating curves and measurements showing how accurate predictions we developed. Even the gradient decent curves were providing normal behavior which is a great indicator of the improved dynamic performance.

The bRNN scheduling algorithm we applied in the Resource Blocks RB scheduler provide the best performance ever according to our criteria as the best throughput curves and the best fairness curves among several SNR values was discovered by applying the novel bRNN scheduling algorithm. These results satisfy the promise that such smart e node base should provide.

The future developments could include a QoS metrics when making the scheduling decisions. The primary goal was to provide the proportional fair to the scheduler. It is clear by providing the resource blocks RBs to the UEs who have maximum channel quality indicator. However, this causes too many failures, delays, and discontinuity. These issues can lead to instability of the system performance and its quality of services. This means proportional fair is the real lead, and Modified SOM technique and bRNN scheduler successfully covers all the history in terms of updates to plan the next plate of RBs and cluster them based in this history.

6.2. Future work:

- Indeed, even though we obtained profoundly new refreshing results, we expect more work and improvements are possible in this type of project. The topic examined here are novel contributions to the developing literature, which is relatively lacking in deep and smart algorithms in the scheduling process. On the other side, focusing on new algorithms such as Recurrent Neural Networks has a lot of promise for more smart solutions. There are some points that need more research and analysis:
- Future Step: we are planning to make the algorithm more adaptive towards mapping the Resource Blocks RB to UEs based on the clusters of the channel Quality Factor CQI. This will happen by using the type of data each UE is willing to use in the next TTI, The goal

here is to maximize the cell downlink throughput. Therefore, in the context of SOM, we are seeking the weights Wc that will provide the max throughput.

- In future development process, these adaptive algorithms could be improved into more specific parameters; Some other information that comes with the feedback of the User Equipment, e.g., other QoS matrics. Other parameters that should be included into this algorithm is the Precoding Matrix Indicator as it's effecting the speed of the network in the Down Link. Other parameters and Rank Indicator (RI) could be very important, and their statues for each user should be effecting the priority in the mapping of the Resource Blocks values. After we reached the level of complexity that really touched reality, these parameters are the main gates to present our data in the grid. We can give each parameter a certain weight based on the environment, the need of the User, and target the network that are built to apply.
- Working toward time of scheduling, The Sampling frequency is important toward knowing how many runs we can do for the modified self-organizing Map algorithm at each TTI. This will be outside of the LTE-A downlink level Simulator, because this simulator is providing us with one Channel Quality Indicators CQI in one TTI.
- Recurrent Neural Network RNN: RNN should be prepared for providing a close prediction to the pattern of Channel Quality Indicator CQI of the users, as well as it will be updated based on the real feedback value at each iteration which will be done at each TTI. This work of RNN should be done after a warming up procedure toward RNN make the network adopting the pattern of the users by applying a number of iteration on previous TTIs.
- The other Future work that should be started at this time: Self Organizing should be applied to the higher level performance in the network which is the link between the E-Node B and

back bone of the network and the connection between the E-Node B and the other E-Node B especially using the X2 Link that connects the nodes to each other. As such, work really need to be done to reach the Self-Organized Network.

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