A Q-learning-based Scheduler Technique for LTE and LTE-Advanced Network

Souhir Feki[1], Faouzi Zarai[1] and Aymen Belghith[2]
[1]NTS'COM Research Unit, National School of Electronics and Telecommunications of Sfax, Tunisia
[2]Saudi Electronic University (SEU), Computer Science Department, Saudi Arabia

Keywords: LTE-Advanced, Scheduling Algorithm, Q-Learning, QoS, Fairness.

Abstract: Long Term Evolution Advanced (LTE-A) is a mobile communication standard used for transmitting data in cellular networks. It inherits all principal technologies of LTE such as flexible bandwidth, Orthogonal Frequency Division Multiplexing Access (OFDMA) and provides new functionalities to enhance the performance and capacity. For some time, LTE-A must co-exist with the 2G and 3G cellular networks, so resource management, potential interference, interworking necessities, etc. are an important issues. The Radio Resource Management (RRM) main function is to ensure the efficient use of available radio resources, making use of the available adaptation techniques, and to serve users depending on their Quality of Service (QoS) parameters. In this paper, we propose a novel dynamic Q-learning based Scheduling Algorithm (QLSA) for downlink transmission in LTE and LTE-A cellular network based on the Q-learning algorithm and adaptable to variations in channel conditions. The main objective of the proposed algorithm is to make a good trade-off between fairness and throughput and to provide Quality of Service (QoS) guarantee to Guaranteed Bit Rate (GBR) services. Performances of QLSA are compared with existing scheduling algorithms and simulation results show that the proposed QLSA provides the best trade-off fairness/throughput.

1 INTRODUCTION

LTE-Advanced is the evolved version of LTE that improves network performance and service quality through efficient deployment of new technologies and techniques. It uses new functionalities over the existing LTE cellular systems to offer higher throughputs and better user experience (Flore, 2015).

For a better management of radio resources in LTE-A and to guarantee a better level of QoS for users, Radio Resources Management (RRM) plays a crucial role in attaining the objective. One of the RRM functions is the packet scheduling which has a key role in the network performance as it is responsible for assigning resources between users while considering QoS requirements (Alam, 2015).

The main problem with scheduling in LTE-A is that there is no firm provision included by 3GPP to manage scheduling process, which make it an open subject for researchers.

Several scheduling techniques have been proposed in the literature where the efficient exploitation of radio resources is fundamental to reach the system performance targets and to guarantee the Quality of Service requirements (ITU, 2008).

In this context, we propose a novel scheduling algorithm for downlink transmission in LTE and LTE-A cellular network based on the Q-learning algorithm (Kaelbing, 1996), flexible to system requirements when different trade-off levels of fairness and throughput are required, and adaptable to variations in channel conditions.

The main objective of the proposed algorithm is to make a good trade-off between fairness and throughput. The performance of the new scheduler is evaluated and compared to the Proportional Fair, Maximum Signal-to-Noise Ratio and Round Robin schedulers.

This paper is organized as follows. Section II of the paper describes the LTE-A downlink scheduling and provides a survey on scheduling algorithms in LTE and LTE-A. Section III describes the concept of Q-learning. Section IV describes the proposed scheduling algorithm. Section V presents the

Feki, S., Zarai, F. and Belghith, A.
A Q-learning-based Scheduler Technique for LTE and LTE-Advanced Network.
DOI: 10.5220/0006425200270035
In *Proceedings of the 14th International Joint Conference on e-Business and Telecommunications (ICETE 2017) - Volume 6: WINSYS*, pages 27-35
ISBN: 978-989-758-261-5

simulation results and performance analysis. Finally section VI concludes this paper.

2 RELATED WORK

The multi-user scheduling is one of the major features in LTE-A networks since it is in charge of satisfying QoS of users, generally scheduling algorithms aim to reach maximum throughput while maintaining a certain degree of fairness.

In LTE-A, Resource Block (RB) is the smallest allocated resource unit with a 180 KHZ size in frequency domain, and divided into two slots in time domain, the length of each slot is 0.5 ms. Scheduling decision is made by the eNodeB at each 1ms which represents the length of Transmission Time Interval (TTI) (Piro, 2011).

Multi-users diversity is managed in both frequency and time domains, physical resources are allocated to users in the frequency/time grid over time. Subcarriers are not individually allocated due to signaling restrictions and so they should be aggregated on a RB-basis.

The Medium Access Control (MAC) layer of the eNodeB is the module responsible for scheduling the different users. At every TTI, the eNodeB assigns RBs based on the channel condition feedback received from active users in the form of Channel Quality Indicator (CQI), designating the data rate supported by the downlink channel.

(Hajjawi, 2016) proposed a novel scheduling algorithm based on Packet Drop Rate (PDR) and cooperative game theory mechanisms (Shaply algorithm) (Niyato, 2006) for LTE-A Networks. A two level scheduling scheme is proposed, in first level packets are classified into classes by scheduler according to the PDR and available resources are allocated based on this metric. In the second level, the proposed algorithm forms a combination between classes using the cooperative game theory; available resources are allocated to users in each class based on Shaply algorithm to assure the lowest requirements for high priority traffic while giving a chance for low priority traffic to be served. During the simulation, the algorithm which compared with Exponential-rule (EXP-rule) and Proportional Fairness (PF) algorithms outperforms the two algorithms in terms of throughput, fairness index and delay.

(Chaudhuri, 2016) proposed a novel Multi Objective based Carrier Aggregation scheduling algorithm for LTE-A network. The algorithm's main purpose is to achieve optimal user QoS and better level of fairness by allocating efficiently the required transmission power to the component carriers according to user QoS request. To achieve this purpose, the proposed algorithm defines two objective functions; maximize cell throughput for all users every one milli-second and minimize the power allocation, and tries to solve this optimization problem using the min-max principle (Gennert, 1988). Simulation results reveal that the proposed algorithm gives a lowest cell throughput gain of two times compared with Round Robin (RR), SJS-PF (Fu, 2013), Cross-CC User Migration (CUM) (Miao, 2014), Efficient Packet Scheduling (EPS) (Chung, 2011), also it achieves best PRB utilization and scheduling energy efficiency compared to EPS and RR.

(AbdelHamid, 2015) studied the scheduling problem in LTE Virtual Networks and proposes a Virtual Prioritized Slice (VPS) approach to improve scheduling of resources for Real Time (RT) and Non Real Time (NRT) traffic in LTE Virtual Networks. The algorithm target is to facilitate varied traffic in virtualized LTE networks. It considers two challenges: the first one is ensuring isolation between service providers while serving real time requests as real time traffic is delay sensitive, the second challenge is time varying channel conditions. A two level scheduling scheme is proposed, in first level packets are classified by scheduler according to the type of traffic by creating a virtual prioritized slice which is forwarded to the VPS scheduler to serve all RT requests foremost, then after the RT traffic is scheduled, the NRT traffic is served using proportional fairness scheduling. During the simulation, the algorithm which compared with NVS (Kokku, 2010) and NetShare (Mahindra, 2013) reduces the blocking of real time flows and improves the throughput of non real time flows. However some limitations can be identified for this approach; when the number of real time requests increase, the average throughput of non real time requests decrease since these requests cannot be served only after the total real time requests are all served. In addition allocating a fixed number of RBs for all real time requests (2 RBs) may be insufficient for some real time services, i.e., HD voice and video, and a waste for other services. However, increasing the number of RBs per real time request will affect the total throughput and makes starvation to the non real time flows.

(Bahreyni, 2014) proposed a new scheduling algorithm for LTE networks that supports channel fast variations and aimed to increase the system capacity while keeping the fairness when the number of active users is greater than the number of existing RBs. This algorithm improved cell edge users' performance by according preferences to users who have less bandwidth. During the simulation, the algorithm compared with, Round Robin, Best CQI and Proportional Fair. The results show good level of fairness with of little decrease in the user's throughput and in total system throughput, this indicates that this algorithm is dedicated to assure good level of fairness among users even if we will attain the minimum level of QoS.

(Escheikh, 2014) proposed a new channel-aware scheduling algorithm for downlink LTE system. In order to offer a good trade-off allowing maximizing average throughput while keeping fairness between active users, the algorithm uses a weighting factor in the scheduling metric, accounting for each active user the number of assigned RBs in the previous resource allocations until the instant time (t−1). A three level scheduling scheme is cited, in first level the algorithm supposes that each eNodeB receives the channel feedback information, and then it calculates for each active user the assigned number of RBs over a time interval until (t−1). These two parameters are used to calculate the elements of a matrix M and calculate each time the maximum metric between those of the matrix M, and based on this metric, the algorithm assigns RBs to users. The algorithm is compared to best CQI, Round Robin and MY_SCH_Not_Fair (Talevski, 2012) algorithms, the results show that the algorithm offer better performance and considerable enhancement compared with the other scheduling algorithms.

In dynamic environment, such as wireless network, we cannot predict the system next situation, it will be more efficient to predict the appropriate scheduling rule when no such previous knowledge about users next requirements and channels conditions is available.

Our Q-learning based algorithm purpose is to achieve an optimal use of radio resources with a satisfied level of fairness even in a very dynamic system, by taking into consideration the state of the transmission channel and trying to best adapt to the propagation conditions.

3 Q-LEARNING

Our scheduling algorithm deploys reinforcement learning by applying the concept of Q-learning (Kaelbing, 1996) in both users scheduling and resources allocation phases. In this section, we give the detailed description of this concept.

3.1 Reinforcement Learning

Reinforcement learning is the problem faced by an agent that must learn behaviour through trial and error interactions with a dynamic environment (Kaelbing, 1996). This type of learning can guide agents based on a function of reward/penalty. The agent interacts with its environment by realizing actions and receives in exchange rewards or penalties. The reinforcement learning can be compared to learning by trial and error, in the sense that it allows the agent to learn by interacting with its environment, without having prior knowledge of it, only rewards or penalties will be provided.

3.2 The Concept of Q-Learning

Q-learning is used for dynamic environments. It is one of the best known algorithms for reinforcement learning framework. Its main idea is to reinforce good behaviour and weaken the bad behaviour of an agent by executing its reinforcement function which specifies the estimated instantaneous reward as a function of the actual state and action.

Q-learning is based on the function Q, which applies to an action in a given state: Q (state, action).

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \times \delta_t \qquad (1)$$

$$\delta_t = r_{t+1} + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t) \qquad (2)$$

Where:

Q (s, a): function of evaluation actions.
δ_t: temporal difference error.
α: learning rate, $0 \leq \alpha \leq 1$. It is used to rate the certitude of values previously estimated.
r_{t+1}: immediate reward received from the environment.
γ: the weight affected to future rewards relative to immediate rewards, it is between 0 and 1. If $\gamma = 0$, only the immediate reward will be considered.

The Q-learning algorithm is as follows:

- Initialize all couples *Q(state, action)* to an initial value.
- Execute the action *a* for each state *e*.
- Obtain the corresponding reward/penalty *r*.
- Refresh the value of *Q* using the equation of incremental update defined previously (equation (1)).

4 THE NOVEL Q-LEARNING-BASED SCHEDULER TECHNIQUE ARCHITECTURE

In QLSA our objective is to achieve the best trade-off for user's throughput and fairness, so we chose to give priority to users according to both channel condition and fairness rate.

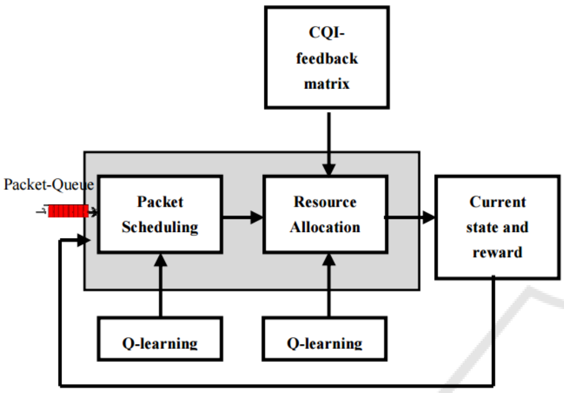

Figure 1: LTE/LTE-A Packet Scheduler Framework.

The current state returns the result of executing the previous scheduling rule in the previous TTI. The immediate reward value gives an objective evaluation about how successful the previous action.

By using the Q-learning, the present action is determined based on the last action-state pair, the current state and immediate reward.

4.1 Packet Scheduling

Our QLSA aims to reach a good relationship throughput/fairness and to provide QoS guarantee to Guaranteed Bit Rate (GBR) services while being suited to the Non Guaranteed Bit Rate (Non-GBR) services.

The technique gives priority to users who will have the best trade-off throughput and fairness in the next TTI. Its principle is to calculate the weighted value of this trade-off for each active user in the network using the reinforcement function of Q-learning.

$$Q_k(t) = Q_k(t-1) + \alpha(r_k(t) - Q_k(t-1)) \quad (3)$$

Where:

$Q_k(t)$: the weighted trade-off of the k^{th} user at time (t).

$Q_k(t\text{-}1)$: the previous weighted trade-off of the k^{th} user.

$r_k(t)$: immediate reward of the environment to the k^{th} user at time (t).

α: learning rate, with $0 \le \alpha \le 1$. More α is greater, more the new reinforcement value will have influence (the current state of the channel will have influence).

To guarantee higher QoS for real time applications, we fortify the current state of the channel by using α>0.5 for GBR traffic, thus channel conditions of GBR users at time t will have more influence, as we consider:

$$\begin{cases} \alpha > 0.5 \; for\ GBR\ traffic \\ \alpha < 0.5 \; for\ Non-GBR\ traffic \end{cases}$$

The term γ describing the future reward is ignored, we consider only the immediate reward because the reward is mainly determined by the current state of the environment (for $\gamma = 0$).

The immediate reward policy is based on the definition of a user fairness index (*UFI*) to evaluate how close the user's transmission throughput is from its throughput requirement (Rodrigo, 2014), and the normalized user throughput (*N_TH*) which defines the fairness criteria. These two metrics are based on throughput and calculated for each user in the cell.

$UFI_k(t)$ is the ratio between the real achieved throughput and the maximum required throughput for the k^{th} user at time (t). The instantaneous *UFI* is defined as:

$$UFI_k(t) = T_k(t)/T_k^{req}(t) \quad (4)$$

Where $T_k(t)$ is the real achieved throughput and $T_k^{req}(t)$ is the throughput requirement of user k at time (t).

$$N\_TH_k(t) = \frac{T_k(t)}{Fair\_Throughput_k(t)} \quad (5)$$

Where $N\_TH_k(t)$ is the normalized throughput defined as the ratio between the real achieved throughput and the fair throughput of the k^{th} user at time (t).

The immediate reward of the environment is defined as:

$$r_k(t) = \eta * UFI_k(t-1) + (1-\eta) * N\_TH_k(t-1) \quad (6)$$

Where η is the weight that allows the setting of a desired trade-off.

4.2 Resource Allocation

The proposed algorithm assumes that each eNodeB receives every TTI, a channel feedback information matrix (CQI-feedback matrix) with two dimensions (Number Users_Equipement x Resource_Bloc Grid Size). User's feedback $R_{k,n}(t)$ corresponds to the predicted instantaneous achievable rate for the k^{th} user at the n^{th} resource block given by:

$$R_{k,n}(t) = \frac{B}{N} Log_2(1 + SNR) \quad (7)$$

Where B is the total bandwidth and N is the number of sub-carriers (Seo, 2004).

For each RB, the algorithm looks for the maximum value of $T_{k,n}(t)$, the k^{th} user's average data rate at the n^{th} resource block calculated as (Song, 2010):

$$T_{k,n}(t) = (1 - \beta)T_{k,n}(t - 1) + \beta\, R_{k,n}(t) \quad (8)$$

We introduce the Q-learning to calculate the weighted average data rate of active users, which corresponds to the estimated average data rate of user at each resource block in the next TTI. Then we proceed to the incremental update of weighted average data rate by applying the principle of Q-learning.

The new predicted value is calculated by combining the observed average data rate and the previous values stored as shown in equation (9):

$$Q_{k,n}(t) = Q_{k,n}(t - 1) + \alpha(T_{k,n}(t) - Q_{k,n}(t - 1)) \quad (9)$$

Where:

$Q_{k,n}(t)$: the weighted average data rate of the k^{th} user at the n^{th} resource block at time (t).

$Q_{k,n}(t\text{-}1)$: the previous weighted average data rate of the k^{th} user at the n^{th} resource block.

$T_{k,n}(t)$: the immediate reward of the environment showing the user's average data rate at time t at the n^{th} resource block.

α: learning rate, with $0 \leq \alpha \leq 1$.

For each resource block, the algorithm finds the maximum value of $Q_{k,n}(t)$ and scheduler each user in the RB where he would experience the highest value.

This algorithm aims to increase the system's throughput while maintaining the concept of fairness, since it does not consider only the instantaneous throughput and fairness, but it considers all the previous achieved levels.

5 EVALUATION

In this section, the performance of the proposed algorithm is evaluated and compared with traditional scheduling algorithms, Proportional Fair, MaxSNR and Round Robin (Sravani, 2013). The performance parameters used for comparison are: average users throughput, average rate of served packets, fairness, and average queuing delay.

- Jain's fairness index: is obtained by Jain's equation to calculate fairness index among the users (Jain, 1991), calculated as (equation (10)):

$$J\left(x_{1,2}, \ldots\ldots, x_n\right) = \frac{\left(\sum_{k=1}^{n} x_k\right)^2}{n \sum_{k=1}^{n} {x_k}^2} \quad (10)$$

Where x_k is the normalized throughput for k^{th} user and n is the number of users. To achieve the highest fairness index, all users must have the same throughput, and fairness index will be equal to 1.

- Average queuing delay: is the average waiting time that takes for a user to get RB allocation in a TTI. It is calculated as (equation (11)):

$$average\ delay = \frac{1}{T}\sum_{t=1}^{T} \frac{1}{k} \sum_{k=1}^{K} w_k(t) \quad (11)$$

Where:

K: number of users in a network.

T: total simulation time (number of TTIs).

$W_k(t)$: delay of user k at time t.

5.1 Simulation Model Description

We consider a simulation model composed of a single cell of the radius equal to 1.5 km, one eNodeB carrier frequency of 2 GHz, a system bandwidth of 5MHz (where 25 RBs are allocated), and a number of users varying between 10 and 100. The eNodeB is considered to be static, serving video, Voice over IP (VoIP) and File Transfer Protocol (FTP) traffic. Users have random positions and random distribution inside the sector.

We choose a mixed data traffic in order to simulate real traffic and demonstrate the impact of the proposed scheduling algorithm on the QoS of different services.

Power transmission of eNodeB and Bit Error Rate (BER) for all users is 43 dBm. The simulation and configuration parameters are presented in Table 1.

Table 1: Simulation parameters.

Parameter	Value
Cell Radius	1.5 km
Cell topology	Single cell
Channel type	Pedestrian-B
Shadow fading standard deviation	9 dB
Carrier frequency	2 GHz
System bandwidth	5 MHz
OFDM symbols per slot	7
Number of RBs	25 RBs
Traffic model	VoIP, Video, and FTP
VoIP packet generation interval	20 ms
Video packet generation interval	100 ms
FTP packet generation interval	10 ms
VoIP delay threshold	100 ms
Video delay threshold	150 ms
FTP delay threshold	300 ms
UE speeds	between 5 and 50 (km/hr)
Number of eNodeB	1
eNodeB transmission power	43dBm
Number of UEs	10 -100
UE distribution	Random
Simulation length	5000 slot
Time-slot length	1 ms
Scheduling/Allocation resource	Per slot
η	0.5

5.2 Simulation Results Description

Different network statuses have been chosen in order to evaluate our new approach performance in different scenarios.

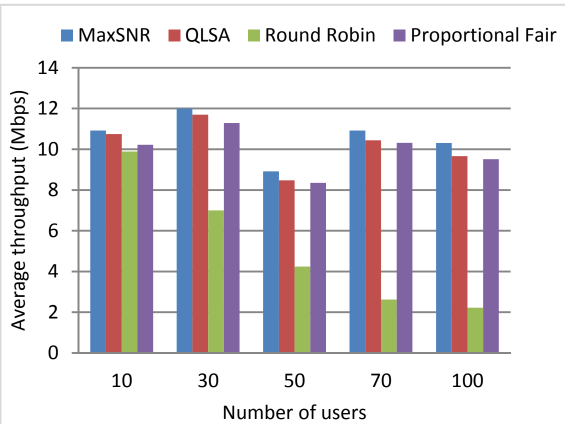

Figure 2: Average user throughput.

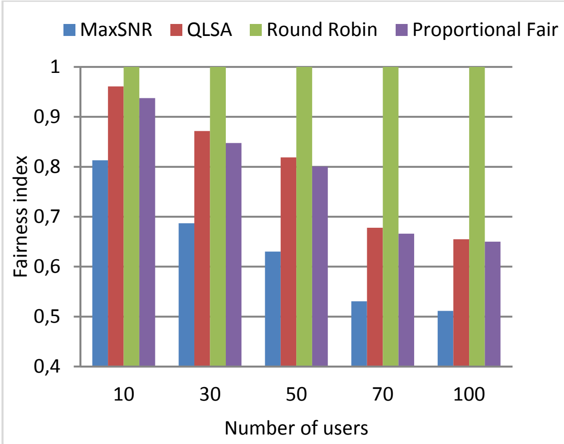

Figure 3: Fairness index.

Figures 2 and 3 show the average user throughput and the achieved fairness index as function of the number of users in the cell. As expected the average throughput of the system with MaxSNR algorithm is the highest as MaxSNR selects the users having the maximum reported SNR value. Therefore, MaxSNR utilizes efficiently the radio resource since it selects packets of users with the best channel conditions. However, this algorithm provides the worst fairness performance, since it prevents users with low SNR from receiving packets until the user's channel conditions will be improved. Contrary to the MaxSNR algorithm, the RR algorithm provides the best fairness index and the worst throughput. To keep balance between throughput and fairness, the PF algorithm was proposed. For the proposed algorithm, we show that QLSA gives the best fairness/throughput trade-off and outperforms PF in both congested and non-congested network. In fact, in the QLSA algorithm, the resources allocation process is triggered according to the history of the channel state of all users in the network, thus it does not depend only on the last state of the channel in order to eliminate discrimination between users with poor or strong channel quality, it considers all the variation in the channel state which brings more fairness. On the other hand, this algorithm gives priority to users with the best channel conditions over the time which improves users' throughput.

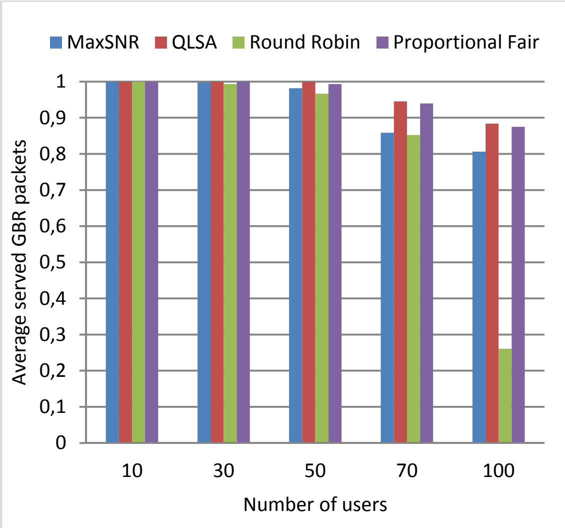

Figure 4: Average rate of served GBR packets.

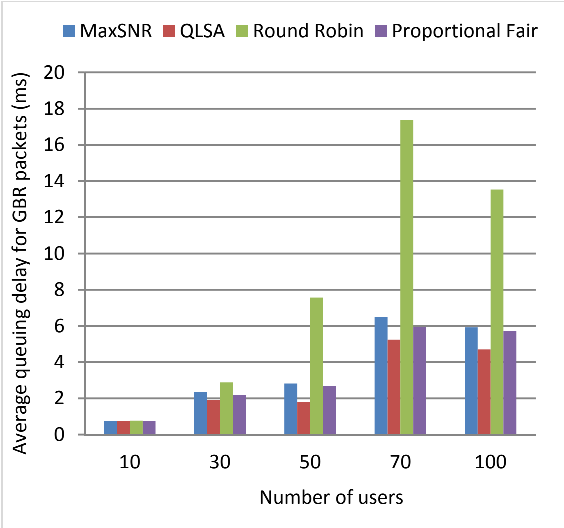

Figure 6: Average queuing delay for GBR packets.

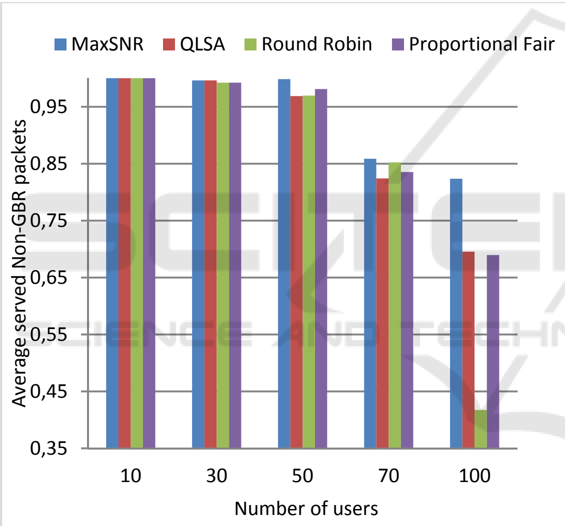

Figure 5: Average rate of served Non-GBR packets.

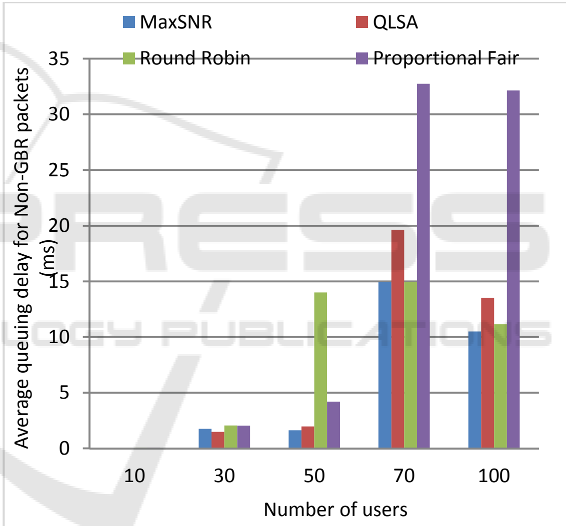

Figure 7: Average queuing delay for Non-GBR packets.

Figures 4 and 5 show the average rate of served GBR and non-GBR packets as a function of the number of users, respectively. For GBR traffic, QLSA reached the best rate since this algorithm distinguishes between GBR and non-GBR traffic. Recall that in QLSA current channel state has more influence for the real time traffic, with $\alpha>0.5$(for the non-GBR traffic $\alpha<0.5$). However, Figure 5 shows that, for the Non-GBR traffic, when the number of users increase, MaxSNR becomes more efficient and outperforms all other algorithms, RR has the worst result while QLSA and PF have comparative results.

Figures 6 and 7 show the average queuing delay for GBR and Non-GBR as a function of the total number of users, respectively. For GBR traffic, QLSA reached the best average delay while RR and MaxSNR show the worst delay. For non-GBR traffic, PF shows the highest average delay followed by QLSA. On the one hand PF does not consider the delay requirements and QLSA does not give priority to non real-time services as this kind of traffic is more QoS requirements-tolerant.

6 CONCLUSION

Maximizing throughput is a target feature of scheduling strategies, but there are other important problems that must be taken into consideration. Fairness is one of these problems that may resist throughput maximization. A trade-off between performance and fairness when implementing scheduling in wireless networks is found.

In this paper, we proposed a novel resource scheduling algorithm based on the Q-learning algorithm for LTE and LTE-A downlink. The proposed scheduler considers two types of traffic: Guaranteed Bit Rate and Non Guaranteed Bit Rate. Simulation results show that the proposed QLSA provides a good trade-off between fairness and throughput; it outperforms other packet scheduling algorithms with a higher rate of served packets and a better queuing delay for GBR traffic. The use of Q-learning makes our technique efficient and opens new perspectives to solve different issues in LTE-A scheduling, so it is interesting to adapt the Q-learning neural algorithm in scheduling for the fifth generation (5G) cellular wireless systems as future work.

REFERENCES

Flore, D., 2015. Evolution of LTE in Release 13. [Online] available: http://www.3gpp.org/news-events/3gpp-news/1628-rel13.

Alam, M., Ma, M., 2015. Radio Resource Management by Evolutionary Algorithms for 4G LTE-Advanced Networks. In *book: Bio-Inspired Computation in Telecommunications*, pp.141-163. Morgan Kaufmann, ISBN: 9780128017432.

International Telecommunication Union (ITU), 2008. Overall network operation, telephone service, service operation and human factors, ITU-T Recommendation E.800 Annex B.

Kaelbing, L., Littman, M., Moore, A., 1996. Reinforcement learning: a survey. In *Journal of Artificial Intelligence Research,* vol.4, pp: 237–285.

Piro, G., Grieco, L. A., Boggia, G., Capozzi, F., Camarda, P., 2011. Simulating LTE cellular systems: an open-source framework. In *IEEE Transactions on Vehicular Technology*, vol. 60, no. 2, pp: 498 - 513.

Hajjawi A., Ismail M., Abdullah, N., Nordin, R., Ertuğ, O., 2016. A PDR-Based Scheduling Scheme for LTE-A Networks. In *Journal of Communications*, vol. 11, no. 9, pp: 856-861.

Niyato, D., Hossain, E., 2006. A cooperative game framework for bandwidth allocation in 4G heterogeneous wireless networks. In *IEEE International Conference on Communications*, Turkey, pp: 4357-4362.

Chaudhuri, S., Baig, I., Das, D., 2016. QoS aware Downlink Scheduler for a Carrier Aggregation LTE-Advance Network with Efficient Carrier Power Control. In *IEEE Annual India Conference*, India.

Gennert, M. A., Yuille, A. L., 1988. Determining The Optimal Weights In Multiple Objective Function Optimization. In *Second International Conference on Computer Vision*, USA, pp: 87–89.

Weihong F., Qingliang, K., Yue, Z., Xin, Y., 2013. A Resource Scheduling Algorithm Based on Carrier Weight in LTE-advanced System with Carrier Aggregation. In *Wireless and Optical Communication Conference*, China, pp: 1-5.

Miao, W,. Min, G., Jiang, Y., Haozhe W, X., 2014. QoS-aware resource allocation for LTE-A systems with carrier aggregation. In *Wireless Communications and Networking Conference*, Turkey, pp: 1403-1408.

Chung, Y. L., Jang L. J., Tsai. Z., 2011. An efficient downlink packet scheduling algorithm in LTE-Advanced systems with Carrier Aggregation. In *Consumer Communications and Networking Conference*, USA, pp: 632-636.

AbdelHamid, A., Krishnamurthy, P., Tipper, D., 2015. Resource Scheduling For Heterogeneous Traffic in LTE Virtual Networks. In *IEEE Conference on Mobile Data Management*, Pittsburgh, PA, pp: 173-178.

Kokku, R., Mahindra, R., Zhang, H., Rangarajan S., 2010. Nvs: a virtualization substrate for wimax networks. In *the sixteenth annual International Conference on Mobile Computing and Networking*, USA, pp: 233–244.

Mahindra, R., Khojastepour, M. A., Zhang, H., Rangarajan, S., 2013. Radio Access Network sharing in cellular networks. In *the IEEE International Conference on Network Protocols*, Germany, pp: 1-10.

Bahreyni, M. S., Naeini, V. S., 2014. Fairness Aware Downlink Scheduling Algorithm for LTE Networks. In *Journal of Mathematics and Computer Science*, vol 11, no. 1, pp: 53-63, pp: 53-63.

Escheikh, M., Jouini, H., Barkaoui, K., 2014. Performance analysis of a novel downlink scheduling algorithm for LTE systems. In *the international Conference on Advanced Networking Distributed Systems and Applications*, Algeria, pp: 13-18.

Talevski, D., Gavrilovska, L., 2012. Novel Scheduling Algorithms for LTE Downlink Transmission. In *Telfor Journal*, vol. 4, no. 1, pp: 45-56.

Rodrigo, F., Cavalcanti, P., 2014. *Resource Allocation and MIMO for 4G and Beyond*, Springer-Verlag, New York. 1st edition. ISBN: 978-1-4614-8056-3.

Seo, H., Gi, L. B., 2004. A Proportional Fair Power Allocation for Fair and Efficient Multiuser OFDM Systems. In *Global Telecommunications Conference*, USA, pp: 3737-3741.

Song, L., Shen, J., 2010. *Evolved Cellular Network Planning And Optimization For UMTS and LTE,* CRC Press. ISBN 9781439806494.

Sravani, S., Jagadeesh, B. K., 2013. Scheduling Algorithms Implementation for LTE Downlink. In *the international Journal for Research in Applied Science and Engineering Technology*, pp: 74-80, vol. 1, No. 4.
Jain, R., 1991. *The art of computer systems performance analysis: techniques for experimental design, measurement, simulation and modeling*, John Wiley & Sons, New York. ISBN: 978-0-471-50336-1.