Load Balancing in Heterogeneous Network Using Machine Learning Technique

L. Rajesh, K.Bhoopathy Bagan,Tamilarasan. K,Meena. M

Abstract:In heterogeneous network load balancing is a major challenge in dense environment. In conventional method of user association, the base station to which the users get service from is determined by the SINR value. In dense environment there would be many pico and femto base stations available with low load the user may receive maximum SINR from the macro base station. This will cause over loading in the macro base station which will in turn reduces the Quality of service for the user. In this paper the load balancing is achieved by user association with the optimal BS that is determined with various factors such as SINR, service fairness, available resources, mobility of user, channel quality to improve the overall service rate and to reduce the variance in the service rate between users. A reinforcement learning algorithm is proposed with variance is service rate as the reward function and by considering the problem as N-arm bandit problem the load is balanced between the various base stations available by providing a good Overall service rate to the users.

Index Terms: Reinforcement Learning, Heterogeneous Networks, Load Balancing, N-arm bandit

I. INTRODUCTION

The data consumption in the wireless networks is increasing rapidly at an alarming rate. This is because the users are downloading and sharing data, at an ever increasing rate, in form of videos, photos, text etc. generally using smartphones and tablets. The ease of access and use of these devices is also contributing to this exponential growth in data consumption.

Heterogeneous network consists of macro base stations and low power base stations like pico, femto etc. Small BSs are added to provide connections in the dead zones, to improve user performance in hot spots with high user demand [18]. By offloading from large macro cell, work performance and QoS has been improved. In Conventional base stations which have high SINR will be solved by users. This creates overload at the macro BS. To avoid this problem a load balancing algorithm is required in heterogeneous network to attain the goal of improved QoS[14], But in real world scenario the user mobility will cause greater impact in the load balancing and hence the QoS.

Revised Manuscript Received on June 05, 2019

L.Rajesh,Department of Electronics Engineering, MIT, Anna University, Chennai, Tamilnadu, India.

K.Bhoopathy Bagan, Professor, Department of Electronics Engineering, MIT, Anna University, Chennai, Tamilnadu, India

Tamilarasan.K, Department of Electronics Engineering, MIT, Anna University, Chennai, Tamilnadu, India.

Meena.M, Department of Electronics Engineering, MIT, Anna University, Chennai, Tamilnadu, India.

If there are some changes in the network environment, the traditional association algorithms must rerun this would cause high cost and also this may lead to poor association in case of highly dynamic environment.The problem of load balancing can be well defined by Reinforcement learning because it has trial-error search and delayed reward. This is highly applicable in our heterogeneous environment where the dynamic nature of the environment is to be tracked to provide more appropriate solution.

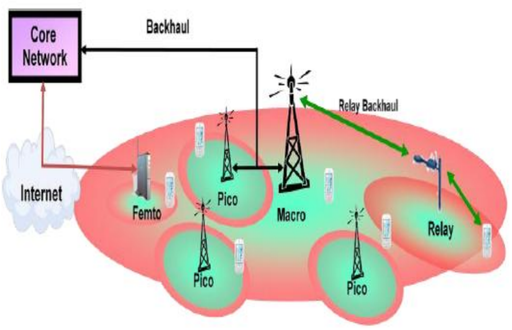

Fig.1. Heterogeneous Network

The study done by Andrews et al. in [4] explains the various myths leading to load imbalance in heterogeneous networks and solutions are analyzed and compared to obtain load balancing. Jiang et al. in [3] have cited the various algorithm of machine learning application in next generation wireless networks. Ye et al. in [9] investigates the cell associated problem with optimal solution The approach in is based on traffic transfer. They propose a user association schemes that achieve load balancing in HetNets through a network-wide utility maximization problem. In [9] Autonomic Load Balancing (ALB) technique is proposed, which are solved by using machine learning techniques, this improves the system capacity significantly but their greed for computing power, need for coordination between the different autonomic processes during and after learning and sometimes longer time will cause disadvantage.

Chen et al. in [11], The framework for the problem of traffic offloading in a stochastic heterogeneous cellular network is proposed. where the time-varying traffic in the network can be offloaded to nearby small cells. Bejerano et al. in [12] present a new load balancing technique by controlling the covering range of WLAN cells. It only requires the ability of dynamically changing the transmission power of the AP beacon messages.

II. SYSTEM MODEL

In heterogeneous environment is considered

Published By:
Blue Eyes Intelligence Engineering & Sciences Publication

with macro, pico and femto base stations. Load balancing is achieved using user association. It is assumed that each user associates exactly with one base stations at a time i.e., multiple associations are avoided since in real time scenario multiple association will not be efficient [14].

Let B denotes the base station and U denotes the user. The achievable rate for the user is defined as

$$C_{ij} = \log_2(1 + SINR_{ij}) \quad (1)$$

$$SINR_{ij} = P_j g_{ij} / \sum_{k \in B, k \neq j} P_k g_{ik} + \sigma^2 \quad (2)$$

Where P_j be the transmit power of BS (j), σ^2 be the noise power level, g_{ik} be the channel gain between user i and BS k.

The key metric for load balancing cannot be simply SINR since this would lead to load imbalance. The metric used in this paper to denote the parameter of load balancing is long term service rate of the user. It is given as

$$R_{ij}(t) = f_{ij}(t) \int_{t0}^{t} x_{ij}(\tau) c_{ij}(\tau)\, d(\tau) \quad (3)$$

Where $f_{ij}(t)$ denotes the amount of resource allocated to the user i by the BS j and it is given by

$$f_{ij}(t) = \sum_{\tau=t0}^{\tau=t} x_{ij}(\tau)/t - t0 \quad (4)$$

Where $x_{ij}(\tau)$ denotes the scheduling factor i.e., $x_{ij}(\tau) \in \{0,1\}$, t denotes the current time, t0 denotes the initial time and the time variable is denoted as τ where $t0 \leq \tau \leq t$

Overall service rate of the network is given as

$$\sum_{i \in B} \sum_{j \in U} R_{ij}(t) \quad (5)$$

In the proposed method load balancing in heterogeneous network is achieved by reinforcement learning. Its objective is to increase the overall service rate and at the same time it also works to reduce the variance between the service rate of the users to provide a fair resource allocation among the users.

III. PRELIMINARY REVIEW ON REINFORCEMENT LEARNING

A brief review on the basic idea of reinforcement learning adopted is given.

A policy maps the actions to be taken for the perceived states of the environment [14]. Let S be the state space and A be the action space, a policy π (s, a) can be defined as the probability of choosing action a in states. In reinforcement learning problems, the environment is unknown. An input s is received from the environment in the reinforcement learning system. These states are estimated based on the model and action is a made. The environment creates new states based on the action a. This state action pair gets a reward based on the reward function designed and it is fed back in to the agent. The agent chooses the next action is based on the current state and the reward value. increasing the positive reward value is chosen for action. The objective of a reinforcement learning agent is to maximize the total rewards it receives in the long run.

In proposed method the environment considered is unbalanced heterogeneous network that initially uses the max SINR method for user association. Reward function is given in (11). Thus the heterogeneous network is modelled using reinforcement learning algorithm.

IV. PROPOSED METHOD

The proposed method for load balancing is discussed. Fig.2. shows the flow chart of the proposed method.

A. Initialization

Initialization is a process in which the basic heterogeneous network is formed for reinforcement learning to apply. Learning procedures generally requires data sets. Hence this phase includes collection, pre-processing and the capturing the area for experiment. The base stations are also located in this phase.

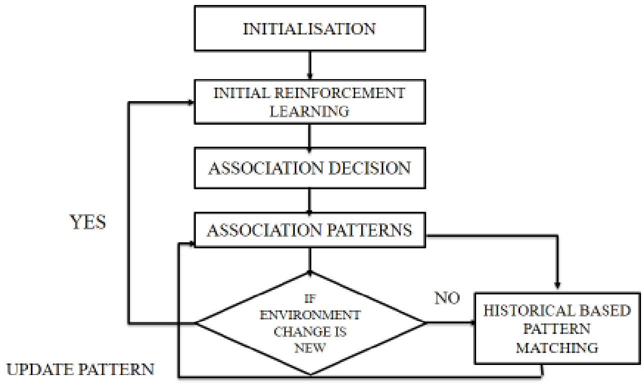

Fig.2. Block Diagram of the proposed method

1. Data Set Collection

The dataset collected contains GPS location of user with a time stamp. The data is collected from 500 users over a month. The database contains continuous updating that gives us the trace of the mobile users. Each dataset contains latitude, longitude of the user location. The dataset collected is in the text format and hence converted to .csv file to give input to the python programme. It may contain some blank spaces and it has to be deleted to make the file eligible for input. The dataset contains some noisy data and are eliminated in the pre-processing.

2. Data pre-processing

The pre-processing is included to eliminate the noisy data sets. Time Location paradigm is used to eliminate the noisy data. That is the user with the available speed cannot move from one location to a very far locations and then come back to the same location within the stipulated time. This idea is used to eliminate the noisy data from the data sets. The area under consideration is longitude -123 to -122 and latitude 37 to 38. This perimeter is used to eliminate the noisy data by deleting the data that exceeds this value within the stipulated time

3. Area capturing

Area under the traces of the user is plotted and the experimental area with maximum density is chosen. The captured area for experiment is Latitude [37.7 37.8] Longitude [-122.3 -122.5]

4. Locating Base Stations

The area captured is measured and based on the area base stations are placed. The base stations used are Macro, Pico and Femto. Macro BSs are given with a coverage area of 10Km. The dead spots are covered by the Pico BSs. The Femto BSs are placed randomly since these BSs are user deployed in areas to improve their data rate. 20 base stations are located in the captured area i.e., 10 Femto BS, 5 Pico BS and 5 Macro BS

B. Initial Reinforcement Learning

1. Initialisation in Reinforcement Learning

The location of the user from the database and the location of the BSs from Table 1,2 and 3 are used to calculate the distance. The locations are in the degree form and the distance should be calculated in kilometre. The conversion if done using (5), (6) and (7)

$$a = (\sin(lat/2))^2 + (\cos(lon/2))^2 * (\cos(lat/2))^2 \quad (6)$$

$$c = 2 * \tan^{-1}(\sqrt[2]{a/(1-a)}), \quad (7)$$

$$d = R * c, \quad (8)$$

Where d denotes the distance, lat denotes the latitude in radians, londenotes the longitude in radians.

TABLE 1 LOCATION OF FEMTO BSs

Longitude	*Latitude*
-122.3517	37.68389
-122.3522	37.67561
-122.4135	37.68415
-122.3093	37.70679
-122.3874	37.70261
-122.2867	37.79085
-122.4359	37.68116
-122.374	37.72064
-122.3372	37.68457
-122.409	37.71535

TABLE 2 LOCATIONS OF PICO BSs

Longitude	*Latitude*
-122.3989	37.77174
-122.3287	37.78139
-122.406	37.74337
-122.2660	37.73806
-122.4051	37.69519

TABLE 3 LOCATIONS OF MACRO BSs

Longitude	*Latitude*
122.2878	37.72992
122.3751	37.78139
122.3394	37.77665
122.3113	37.67921
122.3594	37.74665

Each user measures SINR by (2), calculates service rate by (1) and sent it to the base stations. Base stations calculate the Price value. Price value can be negative. Price value of base station j is μ_j

$$\mu_j = D_j - K_j , \quad (9)$$

where K_j denotes the service supplies available at base station j as given in the Table IV and D_j denotes the service demand on base station j

Decision value is given by d_{ij}

$$d_{ij} = c_{ij} - \mu_j \quad (10)$$

Algorithm 1 Reinforcement Learning

1. Every base station calculates its own decision value

$$d_{ij}(t) = c_{ij}(t) - \mu_j(t) \quad (11)$$

The base station sends this value to the users

2. Each user finds the maximum value among the received value and corresponds them to that station.

$S_j(t)$- set of users associated with base station j at time t

3. Every base station calculates its own reward function

$$\boldsymbol{r_j} = \frac{\mathbf{1}}{\sum_{i=1}^{s_j}\left(\frac{1}{s_j}\right).\left(\boldsymbol{R_{ij}} - \sum_{k=1}^{B}\sum_{i=1}^{V}\boldsymbol{R_{ik}}\right)^2} \quad (12)$$

$\boldsymbol{r_j}$ - Average service rate deviation of user's

4. Calculate the long term cumulative reward

$$\boldsymbol{Q_j(t)} = \frac{\boldsymbol{Q_j(t-1) * count + r_j(t)}}{\boldsymbol{count + 1}} \quad (13)$$

5. Then the price value is adjusted.
   i. If the following condition is satisfied the price value is maintained.

$$\boldsymbol{r_j} \geq \frac{\sum_{k\in B, k\neq j}\boldsymbol{r_k(t)}}{|\boldsymbol{B}| - \mathbf{1}} \quad (14)$$

   ii. Else if the deviation $\boldsymbol{R_j}$ is high, reduce the price value by $\boldsymbol{\delta}$
   iii. Else increase the price value by $\boldsymbol{\delta}$

6. The final association results attain when the following condition is satisfied else the steps iterate

$$|\boldsymbol{Q_j(t) - Q_j(t-1)}| \leq \epsilon \quad (15)$$

Published By:
Blue Eyes Intelligence Engineering & Sciences Publication

7. The achievable rate $\boldsymbol{c_{ij}(t)}$ is updated if the following conditions is not satisfied

$$\left|c_{ij}(t) - c_{ij}(t-1)\right| < \rho \qquad (16)$$

$\boldsymbol{\rho}$ – is a small positive number

Each base station has SINR matrix and Association matrix with dimension U×B. SINR matrix consists of c_{ij} value. Association matrix consists of value {0,1} when the user i connects to the base station j then the matrix value in the association matrix at i,jth position is 1 else it will be zero.

Algorithm 1 is executed in each base stations and the association pattern that it attains shows the balanced user for the base station. Each base station requires information such as service rate and price value to calculates its decision value. The decision value shows the utility the user attains if it gets connected to the particular base station.

C. Historical Pattern Matching

Using the Association pattern, a similarity for present and previous pattern is calculated. If similarity is less than λ, the initial reinforcement learning is initialised. Else it chooses the pattern with maximum similarity.

Algorithm 2 Similarity Function

1. Sort the column k of the matrices $C_{p'}^{k}$, C_{p}^{k}
2. The Pearson distance between vec(k,p') and vec(k,p) is calculated
3. Set $w(k,p') = \sum_{j=k} c_{ij}, c_{ij} \in C_{p'}^{k}$ (17)
4. Set $w(k,p) = \sum_{j=k} c_{ij}, c_{ij} \in C_{p}^{k}$ (18)
5. Set $W(p',p) = {w(k,p')}/{w(k,p)}$ (19)
6. $U(p',p) = {\mu_{p'}^{k}}/{\mu_{p}^{k}}$ (20)
7. calculate the Kullback – Leibler distance $KL\left(W(p',p)\, U(p',p)\right)$
8. Output = $\alpha.\, PD - \beta.KL$ (21)

V. SIMULATION RESULTS

This chapter enumerates the simulation output of the proposed method. Table 4 shows the required simulation parameters.

TABLE 4 SIMULATION PARAMETERS

Parameters	*Value*
Resource supply	110 users per BS
ϵ (Greedy algorithm parameter)	0.001
λ (Similarity Parameter)	0.025
α (weightage value for Pearson Distance)	0.5
β (weightage value for KL Distance)	0.5

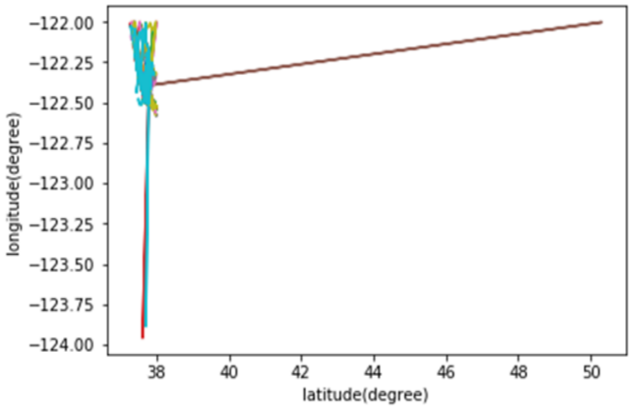

Fig.3. Noisy data sets

Fig.3. shows the noisy data before pre-processing. The spikes show the noisy data available in the datasets. Fig.4. the traces of the mobility user in the entire area. Each colour specifies the movement of each user. Fig.5. shows the placement of BS is the captured experiment area. It consists of 5 Macro Base Station, 5 Pico Base Station and 10 Femto Base Stations.

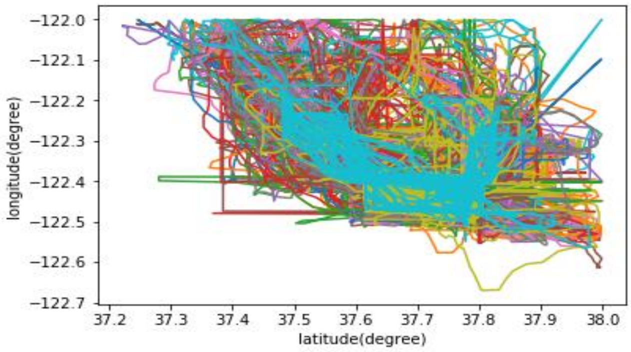

Fig.4. Traces of user mobility

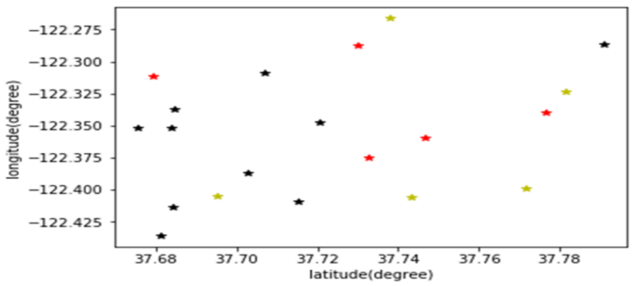

Fig.5. Locations of Base stations

Fig.6. shows the network with mobility traces. Fig.7. shows the comparison between the price adjustment value (δ) and the convergence time required for the initial reinforcement learning to get converge. This shows that for the value of 0.0002 of δ the convergence time reaches the low value. If δ value is further increased the reinforcement learning does not converge.

Published By:
Blue Eyes Intelligence Engineering & Sciences Publication

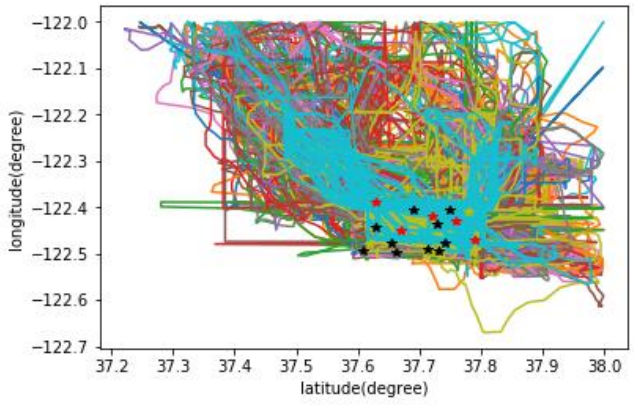

Fig.6.Network with mobility traces

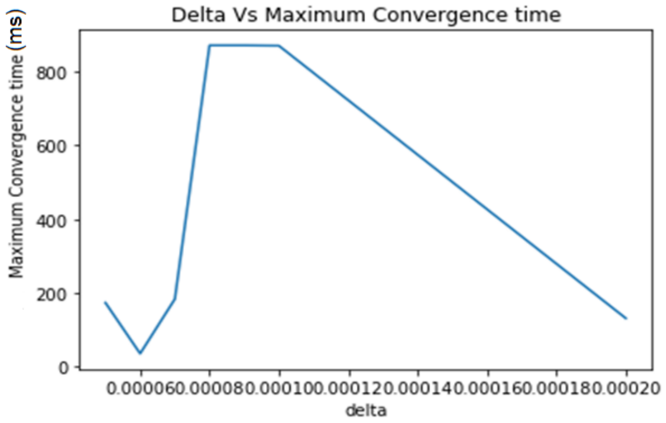

Fig.7. Delta Vs Maximum Converge Time

Fig.8. shows the comparison between the price adjustment value (δ) and the variance of overall service rate. This shows that for the value of 0.0002 of δ the variance is small. Reducing the price adjustment value (δ) will produce higher variance.

Comparing the graphs in Fig.7. and Fig.8. It is concluded that the optimum price adjustment value (δ) is 0.002.

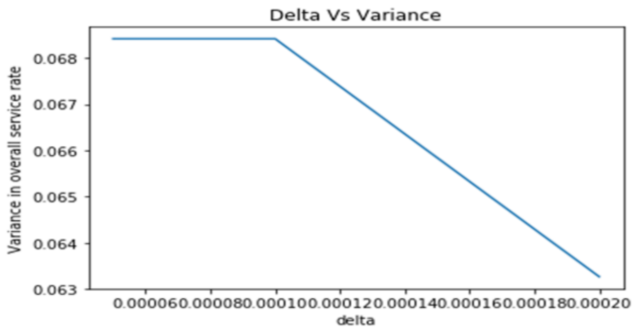

Fig.8. Delta Vs Variance in overall service rate

Fig.9. shows the comparison of loads between the max SINR algorithm and the reinforcement laerning algorithm.

In max SINR algorithm the macro base station is overloaded and the femto base stations are sparsely used. This will cause reduced overall service rate. In the proposed algorithm after the convergence time the load is evenly distributed, also the overall service rate is maintained and frequent handovers are reduced since the mobility of the users are also taken under consideration.

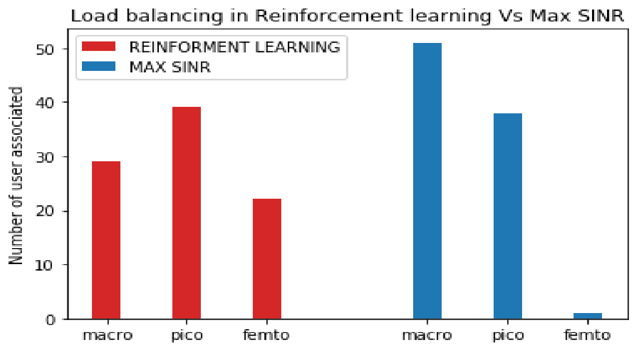

Fig.9. Load balancing Comparison between max SINR and Reinforcement learning

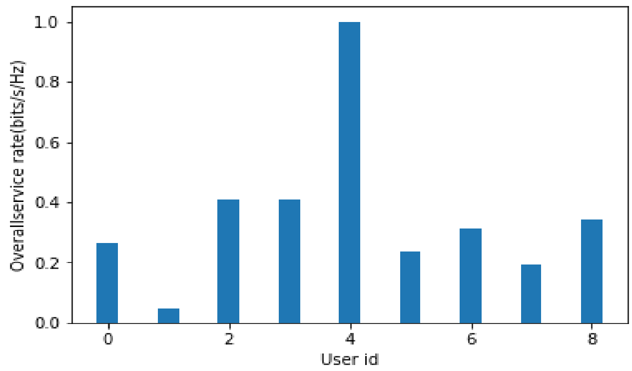

Fig.10. Overall service rate distribution

Fig.10. shows the overall service rate distribution between 10 users in the network. It is shown that the service rate is distributed and the variance is low between the service rates.

VI. CONCLUSION AND FUTURE WORK

Load balancing is a major challenge in the heterogeneous network that will decides the Quality of service offered by the network at peak hours it would decides the service availability to the users. In this paper a reinforcement learning algorithm is designed to intelligently and continuously learn from the environment, the price value is fixed such that the convergence time of the learning process and the variation between the user service rates are low and to associate the user to the base stations so that they get higher overall service rate. The load is balanced well between the base stations. In Future work, proposed method can be extended by increasing the area of the network, users pinging rate to the base stations. The work can also include the backhaul constraints when connecting the femto cell to the core network.

REFERENCES

1. Chunxiao Jiang, HaijunZhang, YongRen, Zhu Han, Kwang-Cheng Chen, LajosHanzo "Machine Learning Paradigms for Next-Generation Wireless Networks", IEEE Wireless Communications Volume. 24, Issue.2, pp .98-105 (2017)
2. Duong D. Nguyen, Hung X. Nguyen, Member, IEEE, and Langford B. White, Senior Member, IEEE, "Reinforcement Learning with Network-Assisted Feedback for Heterogeneous RAT Selection", IEEE Transactions On Wireless Communications, Volume: 16, Issue: 9, pp. 6062 – 6076 (2017)

3. Hye-Young Kim,Jong-Min Kim “A load balancing scheme based on deep-learning in IoT”, Cluster Comput 20,pp .873–878 (2017)
4. Jeffrey G. Andrews, Sarabjot Singh, Qioayang Ye, XinqinLin,andHarpreet.S.Dhillon “An Overview Of Load Balancing In HetNets:Old myths and open problems”, IEEE Wireless Communications pp .18 – 25 (2014)
5. Mohd. Shabbir Ali, Pierre Coucheney, and Marceau Coupechoux ,“Load Balancing in Heterogeneous Networks Based on Distributed Learning in Potential Games”, 13th International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks (WiOpt), pp . 371- 378 (2015)
6. P. Kolios, K. Papadaki, and V. Friderikos, “Efficient cellular load balancing through mobility-enriched vehicular communications,” IEEE Trans. Intell. Transp. Syst., vol. 17, no. 10, pp. 2971–2983 (2015)
7. Pablo Munoz, Raquel Barco, JoseMaria Ruiz-Aviles, Isabel de la Bandera, and Alejandro Aguilar “Fuzzy Rule-Based Reinforcement Learning for Load Balancing Techniques in Enterprise LTE Femtocells”,IEEE Transactions Vehicular Technology, vol.62, No. 5, pp .1962-1973 (2013)
8. PlamenSemov, PavlinaKoleva, KrasimirTonchev, Vladimir Poulkov ,AlbenaMihovska , “Autonomous learning model for achieving multi cell load balancing capabilities in HetNet”, IEEE International Black Sea Conference on Communications and Networking, pp .1-5 (2016)
9. Q. Ye, B. Rong, Y. Chen, M. Al-Shalash, C. Caramanis, and J. G. Andrews, “User association for load balancing in heterogeneous cellular networks,” IEEE Trans. Wireless Commun., vol. 12, no. 6, pp. 2706–2716 (2013)
10. SetarehMaghsudi and SławomirSta´nczak, “Channel Selection for Network-Assisted D2D Communication via No-Regret Bandit Learning with Calibrated Forecasting”, IEEE Transcations on Wireless Communications, Vol.14, N0. 3, pp.1309 – 1322 (2015)
11. X. Chen, J. Wu, Y. Cai, H. Zhang, and T. Chen, “Energy-efficiency oriented traffic offloading in wireless networks: A brief survey and a learning approach for heterogeneous cellular networks,” IEEE J. Sel. Areas Commun., vol. 33, no. 4, pp. 627–640 (2015)
12. Y. Bejerano and S. J. Han, “Cell breathing techniques for load balancing in wireless LANs,” IEEE Trans. Mobile Comput., vol. 8, no. 6, pp. 735–749 (2009)
13. Ying Li, Zhouyue Pi, Lingjia Liu “Distributed Heterogeneous Traffic Delivery over Heterogeneous Wireless Networks” IEEE ICC 2012 - Wireless Networks Symposium, pp. 5332 – 5337 (2012)
14. Zhong Li, Cheng Wang, and Chang-Jun Jiang “User Association for Load Balancing in Vehicular Networks: An Online Reinforcement Learning Approach”, IEEE Transactions On Intelligent Transportation Systems, Volume: 18, Issue: 8,pp. 2217 – 2228 (2017)
15. Parag Kulkarni “Reinforcement and Systemic Machine Learning for Decision Making” IEEE Press 2012 Published by John Wiley & Sons, Inc., Hoboken, New Jersey (2012)
16. R. S. Sutton and A. G. Barto,” Reinforcement Learning: An Introduction” Cambridge, MA, USA: MIT Press (1998)
17. http://crawdad.org/epfl/mobility/20090224
18. http://www.3gpporg/technologies.