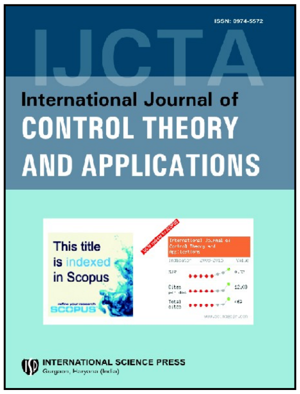

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Self-Organization Load Balancing Technique for LTE and LTE-A Networks

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Abstract: Phenomenal growth in terms of technological revolution and the quantum of usage that has evolved in the wireless technology solutions and services has emphatic load on the wireless networks and the need for robust bandwidth that can serve high quality of services. There is integral need for more effective intervention in infrastructure set up and management of networks for optimal performance. One of the significant issues that impact the performance of a network is the load balancing, and despite of many load balancing solutions available, still there is imperative need for improvement and more effective solutions for robust LET networks. To address the limitations that are considered for the review of literature in the domain, the proposed model of game theory and fuzzy logic based load balancing solution for LTE networks are proposed. In the proposed technique, load balancing is initiated based on every cell status which is evaluated using fuzzy guided game theoretic approach. From the review of the results in simulation studies that are carried out in comparison with certain bench marking models, it is evident that the proposed solution is more result oriented and has shown good results in minimizing the radio link failure and improving the quality of services.

Keywords: Game Theory, Load Imbalance, LTE, Fuzzy Logic, 3GPP, Self-Optimization

1. INTRODUCTION

ICT trends have transformed the way the communication takes place in business and personal communications. The raising trends of mobile communications, voice and data consumption taking place in significant manner and the evolution of Internet of Things (IoT) has raised more consumption of bandwidth distribution on cells. In the current scenario, with majority of the solutions on rise with the quantum of load on network cells are very high. The way, certain cells in the network are being overloaded, while some certain network cells are being idle, issues pertaining to resource utilization factors creep up and impact the band width management and QoS for active users. Issues of load balancing has significant impact on the cellular network, and majorly the issues pertaining to resource management, load balancing that affects the performance in the network, and to mitigate such issues of load balancing and improving the performance, there is need for effective load balancing techniques for addressing the issues. Certain contemporary solutions wherein the load information exchange and other such solutions are implemented for effective outcome.

Performance of a network is majorly influenced by several factors that create inter-cell interference (ICI) and the load imbalance. In instance of managing LTE, there is need for robust load balancing, the basic idea of load balancing is to free the excessive traffic from the hot spots and manage such traffic to the neighboring low-load cells. Optimization supports in better utilization of the network towards overall system throughput by QoS to the end users.

In a successful load balancing scheme, there is need for minimizing the radio resources of maximum loaded cell for avoiding the traffic congestion emerging in LTE (Long Term Evolution) networks. If there are any imbalances in the LTE networks, deteriorates the system performance, and there is need for real-time inter-cell optimization adaptable for environment, categorically when it's unbalanced and time varying [3] [5]. Considering such factors, in this paper, fuzzy guided game theoretic approach for load balancing in LTE networks.

1.1. Game Theory Approach

The game Z is defined as Z = (N, S, $\{UF_i\}$).

In which N = finite set of players

S = action space formed as Cartesian product. i.e. $S = S_1 \times S_2 \times S_3 \times S_4 \times S_n$

UF_i = utility functions.

$UF_{i\,=} \{UF_1, UF_2,..,UF_n\}$

Outcomes that are chosen by a specific player i with S_i as UF_i and the specific actions that are chosen by other players is S_{-i}.

In implementation of game theory, rationality is the key assumption. In rationality, it is assumed that players maximize the payoff. In game theory, the solution of the game is about the possible outcome that could be envisaged from the game process. In wireless system networks, IDS (intrusion detection system) is considered as one player and the intruder is considered as the other player considered as an opponent. In WSN problem, larger WSN is divided in to varied clusters and at any point of time, IDS defends a cluster, as the attacker disturbs the normal operations.

The key applications of game theory

Decision making is the key solution for that is adapted in evaluation of varied choices

In the process of network solutions management in effective manner, Power control to set the power level of nodes, the process is carried out to maximize the signal interference to noise ratio (SINR), the selection path using source node for minimizing the delay, cooperation among the nodes finding the service and towards forwarding the packets to their respective destinations.

This paper is organized in the following manner. In continuation to the introduction proposed in section-1, section-2 discusses the related work for of fuzzy guided game theory and in section-3, the fuzzy guided game theory approach for load balancing in LTE. Section-4 defines the experimental results and section 5 discusses the simulation results of the proposed project.

2. RELATED WORK

LI BO et.al [1] has suggested a solution of inter-domain cooperative traffic balancing scheme that targets on reduction of resource cost and mitigation of interference in co-channels in multi-domain het.net. For the process of evaluation, GA (Genetic Algorithm) method is adapted for demonstrating effective resource cost management using the inter-domain traffic balancing scheme. The results from the proposed model are much effective than the intra-domain balancing scheme. Estimations depict that 43% of the resource costs are saved from the proposed model, but the cell-edge throughput and average cell throughput is not effectively increased.

Zahihang Li et.al [2] proposed an algorithm that constitutesQoS aware intra and inter-cell handover and also the call admission control. Algorithm efficiently reduces the blocking rate of a new call for the users with QoS requirements and also improve the total utility for users without any QoS requirements at the cost of a bit degradation for total throughput.

In [3], Ahmed Awada has proposed a solution for load balancing using, game-theoretic analysis for load balancing. In the proposed solution, utility function is modeled for maximization for each player and the action required for Nash equilibrium point is also defined. Load balancing can certainly increase the capacity usage of the network even in the instances of cell acting in a non-cooperative manner. The load acceptance or rejection is independently decided by each cell, and the Nash equilibrium point is achieved with effective load balancing. Such a process leads to scope of considering deployment of varied load balancing algorithms despite there could be some impact on performance which might be of negligible ratio.

In [4], Wenyu LI et.al has proposed model of dynamic hysteresis-adjusting algorithm for self-organization of networks in LTE. Also, it considers the realistic network situations in to account for obtaining more reliable result. Proposed model when assessed by system level simulation, it witness improvement in handing over performance and varied satisfied users in LTE networks.

Omar Altradet.al [6] proposed the model of general load-balancing model for congested cells to handle traffic in dynamic manner. Algorithm can be controlled and triggered when there is need for any cell on the system. It is implemented in a distributed or semi-distributed fashion. Triggering cycle of the algorithm is up to decision of operator to decide upon, based on underlying variations that are slow and there is need for self-optimizing network (SON) algorithms. The load-balancing algorithm for an LTE network vivid criteria is adopted for evaluating algorithms performance.

Munoz [7] has proposed the method of optimizing FLC for load balancing in varied generation wireless networks that are reliant on dynamically handling HO margins. Two varied range of optimization approaches reliant on fuzzy Q-learning algorithm are also considered. UEE each is based on optimization scheme which explore FLC actions based on load balancing process. BEE is the optimization scheme for combining both exploitation and exploration for enhancing performance whilst finding the optimal FLC actions. Also for providing dynamic adaptation for system variations, there is need for robust system. It is imperative that UEE optimization approach is a resourceful method for accurately preserving the call quality constraint, during the load balancing adjusting a call dropping threshold. But in BEE optimization approach, FLC shall select new range of optimal actions that could lead to a lower value of CBR and speeding up the process of load balancing process, whilst preserving same constraint in CDR.

WANG Min et.al [8] suggested a min-max load balancing (LB) model for minimizing demanded radio resources of maximum loaded cell. Multicast services are transmitted using SFN (Single Frequency Network) mode and using the PTP (point to point) mode multicast services are delivered. The min-max LB takes in to account point-to-multipoint (PTM) mode for multicast services and chooses proper transmission model amidst SFN and PTNM for every multicast service for minimizing the demanded radio resources from maximum loaded cell rather than adapting SFN mode for all the multicast services. But the consumption of radio resource increases in the proposed solution.

In [9], Ming Li have proposed an LTE virtualization framework and the dynamic load balancing scheme for multi-eNB and multi-VO (Virtual Operator) systems. The research has also evaluated the parameterization of both schemes including sharing intervals, LB intervals and the safety margins for finding the optimal parameter settings. LTE networks can certainly benefit both NV and also the LB techniques.

Pabalo Munoz et.al [10] has designed numerous load balancing techniques depending on self-tuning of femtocell parameters. Specifically, such techniques are adapted in FLC (Fuzzy logic controllers) and in FRLSs (Fuzzy Rule Based Reinforcement Learning System). Performance assessment is conducted using simulators that are of dynamic system-level. Combination of FRLS and FLC supports in improved performance and better outcome rather than the performance of each of such system in independent manner. Also, the response time and final value of performance indicators are also improved.

3. FUZZY GUIDED GAME THEORETIC APPROACH FOR LOAD BALANCING IN LTE

This paper discusses a contemporary model of game theory and fuzzy logic based technique for load balancing in LTE networks. In the proposed solution, the load balancing is triggered based on position of every cell, which is estimated using fuzzy logic. In the solution, metrics like bandwidth, call blocking ratio, signaling cost and the scope of availability are considered as key inputs for fuzzy logic and the status of cells are determined as output. Depending on cell status, load balancing is triggered and an adjustment of dynamic hysteresis is carried out using the game theory model. Also, a utility function is created using RLF ration and the hysteresis is adjusted automatically to ensure maximum utility.

3.1. The metrics used and their estimation process

Bandwidth (*BW*): has critical objective of the proposed load balancing strategy, depicting the bandwidth available from the respective neighbor cells.

Signaling Cost: The chosen metric indicates the aggregate value in terms of location update costs and the location tracking elements that are discussed in the previous sections (see section 3.2). Such a metric is also very critical for achieving effective outcome and service in load balancing. Assessment of a signaling cost for a cell is estimated using:

$$sc_{N_j} = c_{lt}(N_j) + c_{lu}(N_j)$$

Here sc_{N_j} is the cost of signaling for acell N_j, $c_{1t}(N_j)$ and $c_{lu}(N_j)$ are cost forlocation tracking and cost for location update of the respective cell N_j

Call Blocking Ratio (CBR): Admission controller in the system, depending on the cell status, either accept or decline the requests of respective calls in line for a cell It is imperative from above statement that cell selection optimality is very highly influenced in this metric, and the call blocking ration for a cell N_j is assessed as follows:

$$cbr_{N_j} = \frac{c_d(N_j)}{|C_{Nj}|}$$

In the equation above c_d indicates the number of calls requests declined for cell N_j by admission controller and $|C_{Nj}|$ is cumulative of calls triggered to cell N_j, wherein the aggregate of calls accepted and blocked.

Availability Scope/ Availability Capacity (AC)

The key reasons that lead to failure of a cell towards triggering to respective cell could be attributed to failure of update for a cell. The inverse ration of call establishment failure pertaining to availability scope of a respective cell. Such a metric influence the quality of service, though some of the metrics like bandwidth availability, signaling and other such parameters are in place. It is imperative that for achieving optimal load balancing, the scope of availability plays a vital role and can be estimated using

$$ac_{N_j} = 100 \times \left(1 - \frac{c_{dr}(N_j)}{c_a(N_j)}\right)$$

In the equation above, ac_{N_j} indicates the availability scope of the cell N_j and c_{dr},(N_j), $c_a(N_j)$ denotes respective number of calls accepted or declined by the admission controller for cell N_j.

3.2. Cell Status Estimation using Fuzzy based Solutions

Using the Tabu search powered by fuzzy logic, the cell selection process is performed. For attaining the process, the cell state is estimated using the fuzzy reasoning over the metrics adapted. For enabling the respective fuzzy membership function, fuzzification of adapted metrics shall be carried out as follows:

Values that are observed for metrics are adapted using fuzzing in three vivid ranges like the high, medium and low. Process of fuzzification for every metric is carried out using:

$$avg_{bw} = \frac{\sum_{j=1}^{|NL|} bw_{N_j}}{|NL|}$$

$$mse_{bw} = \frac{\sum_{j=1}^{|NL|} \sqrt{\left(avg_{bw} - bw_{N_j}\right)^2}}{|NL|}$$

$$ft_{bw} = \sqrt{\left(avg_{bw} - mse_{bw}\right)^2}$$

Equations that are observed with average bandwidth avg_{bw} and respective mean square error mse_{bw} of the cells in cells list NL. Here $|NL|$ denotes number cells in cells list. ft_{bw} In the fuzzification threshold of the metric bandwidth availability, comprising absolute difference amidst avg_{bw} and it'srespective nse_{bw} the bandwidth availability fuzzification can be found in table 1.

Table 1
Fuzzification of the metric bandwidth availability of cells

$< ft_{bw}$	Low
$(\geq ft_{bw})$ ^ $(< avg_{bw})$	Medium
$\geq avg_{bw}$	High

$$avg_{sc} = \frac{\sum_{j=1}^{|NL|} sc_{N_j}}{|NL|}$$

$$mse_{sc} = \frac{\sum_{j=1}^{|NL|} \sqrt{\left(avg_{sc} - sc_{N_j}\right)^2}}{|NL|}$$

$$ft_{sc} = \sqrt{\left(avg_{sc} - mse_{sc}\right)^2}$$

Equations detailed identify the average signaling costs avg_{sc} and respective mean square error mse_{sc} of the cells in cells list NL. Here $|NL|$ denotes number cells in cells list. ft_{sc} in the fuzzification threshold of the metric signaling cost, wherein absolute difference between avg_{sc} and its respective mse_{sc}. The signaling costfuzzification can be observed in table 2.

Table 2
Fuzzification of the metric signaling cost of cells

$< ft_{sc}$	High
$(\geq ft_{sc}) \wedge (< avg_{sc})$	Medium
$\geq avg_{sc}$	Low

$$avg_{cbr} = \frac{\sum_{j=1}^{|NL|} cbr_{N_j}}{|NL|}$$

$$mse_{cbr} = \frac{\sum_{j=1}^{|NL|} \sqrt{\left(avg_{cbr} - cbr_{N_j}\right)^2}}{|NL|}$$

$$ft_{cbr} = \sqrt{\left(avg_{cbr} - mse_{cbr}\right)^2}$$

Equations detailed above support in identification of average call block ration avg_{cbr} and respective mean square error mse_{cbr} of the cells in cells list NL. In the equation $|NL|$ denotes number cells in cells list. ft_{cbr} are the fuzzification threshold of the metric call block ratio, with absolute variation amidst avg_{cbr} and its respective mse_{cbr}. The call block ratio fuzzificationcan be found in table 3.

Table 3
Fuzzification of the metric signaling cost of cells

$< ft_{cbr}$	High
$(\geq ft_{cbr}) \wedge (< avg_{cbr})$	Medium
$\geq avg_{cbr}$	Low

$$avg_{ac} = \frac{\sum_{j=1}^{|NL|} ac_{N_j}}{|NL|}$$

$$mse_{ac} = \frac{\sum_{j=1}^{|NL|} \sqrt{\left(avg_{ac} - ac_{N_j}\right)^2}}{|NL|}$$

$$ft_{ac} = \sqrt{\left(avg_{ac} - mse_{ac}\right)^2}$$

Equation observes the average available scope and respective mean square error of the cells in cells list. Here denotes number cells in cells list. is the fuzzification threshold of the metric available scope, that has absolute difference amidst and its respective . The fuzzification of scope of availability can be observed in table 4.

Table 4
Fuzzification of the metric available scope of cells

$< ft_{ac}$	Low
$(\geq ft_{ac}) \wedge (< avg_{ac})$	Medium
$\geq avg_{ac}$	High

3.3. Fitness Criteria (de-fuzzification) for cell selection

The process of de-fuzzification is further carried out to assess the fitness of a cell and the conditions that are adapted for membership function are depicted in table 5 and table 6.

The Fuzzy reasoning further performs defuzzification to estimate the fitness of a cell, the conditions adapted by the membership function are represented in table 5 and 6.

Table 5
Fuzzy reasoning adapted by the membership function to estimate the fitness of the cell

If ((BW is [HIGH || MEDIUM] and SC is [LOW] and CBR is [LOW] and AC is [HIGH||MEDIUM]) or (BW is [HIGH || MEDIUM] and SC is [LOW] and CBR is [LOW||MEDIUM] and AC is [HIGH]) or (BW is [HIGH || MEDIUM] and SC is [LOW||MEDIUM] and CBR is [LOW] and AC is [HIGH])) then fitness is HIGH	**HIGH**
Else If ((BW is [MEDIUM] and SC is [MEDIUM] and CBR is [LOW] and AC is [MEDIUM]) or (BW is [MEDIUM] and SC is [LOW] and CBR is [MEDIUM] and AC is [MEDIUM]) or (BW is [MEDIUM] and SC is [LOW] and CBR is [LOW] and AC is [LOW])) then fitness is MEDIUM	**MEDIUM**
Else in rest of all cases fitness is LOW	**LOW**

Table 6
Tabular representation of the fitness conditions (defuzzification) to select cell

BW	SC	CBR	AC	FITENSS
HIGH||MEDIUM	LOW	LOW	HIGH||MEDIUM	HIGH
HIGH||MEDIUM	LOW	LOW||MEDIUM	HIGH	HIGH
HIGH||MEDIUM	LOW||MEDIUM	LOW	HIGH	HIGH
MEDIUM	MEDIUM	LOW	MEDIUM	MEDIUM
MEDIUM	LOW	MEDIUM	MEDIUM	MEDIUM
MEDIUM	LOW	LOW	LOW	MEDIUM
Rest of all cases	LOW			

3.4. Game Theory Based Load Balancing Technique

Depending on the status of the cell, the load balancing factors are triggered and the hysteresis adjustment is performed dynamically, using the game theory model. Utility function is developed for RLF (Radio Link Failure) ratio and the hysteresis is adjusted in dynamic manner to ensure that the utility is maximum.

Game theory adapted based on load balancing technique is modeled using defining of players and the utility function and also the strategies that are possible.

Let N_1 be the active cell having excess load.

Let N_2 be the passive cell having minimum load

Let a_1 be the lowest level at which RFL ratio is acceptable

Let a_2 be the offset of a_1 ranging from 0 to a_1

The players N_1 and N_2 of the game are at opposite location and ready for gaming.

It constitutes following steps:

1. The game starts at time t

2. The radio link failure is triggered during service interruption.

3. If RLF<(a_1-a_2),

Then

The load balancing is triggered

Else

If (a_1-a_2) <RLF <a_1,

Then

Hysteresis value is adjusted

End if

$$\text{Hysteresis } H_i = \begin{cases} H(i-1)+s & (1) \\ H(i-1)-s & (2) \end{cases}$$

The condition (1) denotes decrement in RLF ratio compared to last adjustment.

The condition (1) denotes increment in RLF ratio compared to last adjustment.

sdenotes the adjustment which is iterative

4. Utility function (UF_i) for the game is the radio link failure (RLF) ratio in the cell. UF_i for N_2 with a ratio a_1 and UF_{i--} 0 is defined by using following equation

$$UF_{N2} = \begin{cases} UF_{N2} + z_i & \text{if} \quad 0 \le \tilde{a}_1 \le 1 \\ \left\lfloor \dfrac{UF_{N2} + z_i}{a_1 + \sum_{j=1}^{z_i} \tilde{A}_j} \right\rfloor, & \text{otherwise}' \end{cases} \tag{7}$$

In which Aj $_=$ approximation value of the RLF ratio

z_i= number of active cells.

5. Depending on value of a_1, N_2conducts the load balancing.
6. The utility function of the N_2 with UF_0>0 users and a_1>1 is estimated with the following set of equation

$$UF_0 = \begin{cases} UF_0 + z_0 & if \quad 0 \le a_1 \le 1 \\ \left\lfloor \dfrac{UF_0 + z_0}{a_1 + \sum_{j=1}^{z_0} A_j} \right\rfloor, & otherwise \end{cases},$$

As the network load is already defined, N_2 easily chosesa$_2$that maximizes the utility function by adjusting the hysteresis value.

4. SIMULATION RESULTS

A dynamic LTE system-level simulator has been developed using javaFX and MXML. The criteria and parameters specified in [12] are used in order to build the simulation (see table 7). Each iteration of the simulation was performed around 20 min, which enables approximately 15000 transmission requests.

Table 7
Parameters used in simulation

Parameter	*Configuration*
Layout measurements of the cellular network	90 cells (4 X 19 regions),
Cellular frequency radius	500 meters
Carrier frequency capacity	2.4 GHz
Max bandwidth capacity	1.4 MHz
Considered Transmission type	Downlink transmission
Propagation properties	Okumura-Hata with wrap-around Log-normal slow fading, ó=8dB, correlation dist=20m
Service properties	real-time variable bit rate service (voice call), Pareto traffic arrival, mean call duration 90s, 16 to 24 kbps
Frequency repeated uses	1
Scheduling properties	Time domain: round-robin Frequency domain: best channel
Channel properties	EPA and multipath model
Mobility type and speed	Random walkof constant speed 2500meters per hour
Handover	Time-To-Trigger = 100 ms, HO margin: -24 to 24dB
Type of the Base station	Tri-satirized antenna: tri-sector, SISO, EIRPmax = 43 dBm
Time resolution	100 ms
Traffic distribution	Haphazardly dispersed in space
No of Requests per iteration	15000
iteration time	20 min

I.1 The Performance Metrics

For assessing the optimality, scalability and the level of robustness for a proposed load balancing method, the metrics like the HFR (Handover Failure Ratio), SCR (Signaling Cost Ratio), CBR (Call Block Ratio) and RLF (Radio Link Failure) ration were considered. Objective of load balancing for minimizing the handover failure, radio link failure and call blocking is essential and such metrics are considered to be impacting the performance analysis. Signaling costs also make a holistic difference to the performance of the proposed solution.

I.2 The Performance Analysis

In the simulation study of the proposed solution, the log of values observed for varied performance metrics at every attempt of cell allocation towards transmission request is analyzed. Ration of performance metric values at fixed intervals are used for assessing the proposed model. To notify the optimality of proposed load balancing using Tabu search algorithm powered by Fuzzy solutions as (FGGT-LB), the values resulting as part of the performance metrics are compared to the other contemporary solutions like DHA[4] and Fuzzy Q [7].

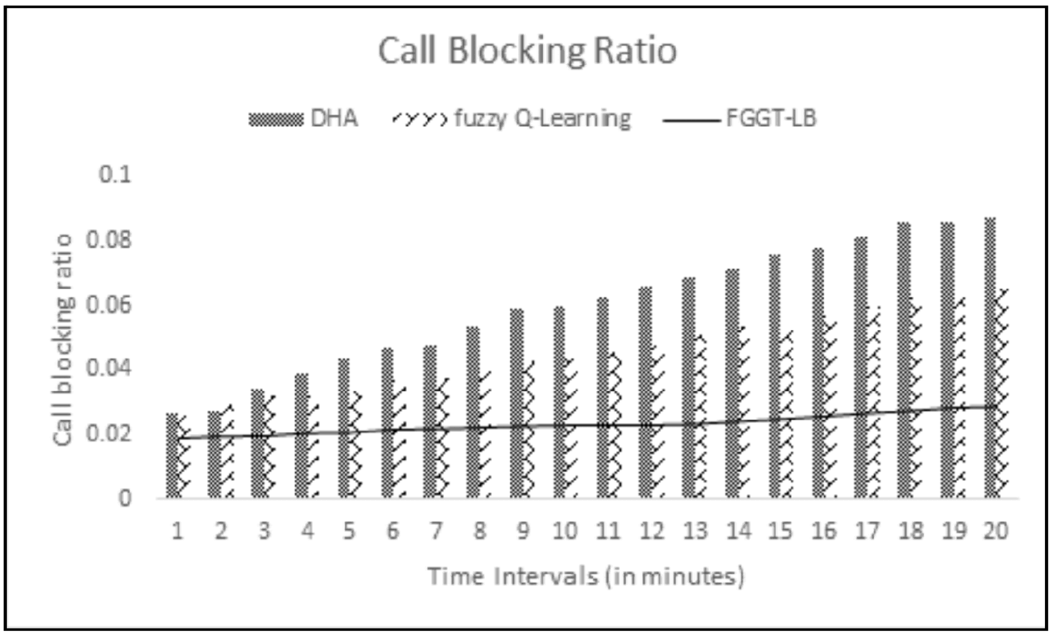

Figure 1: Comparison of call blocking ratio observed for DHA, Fuzzy Q-Learning and FGGT-LB

From the resultant values it is imperative that the call blacking ratio for the proposed model of FGGT-LB is being much lower than the ones that are compared for the other two. Benchmarking models. Load versus call blocking ration of a divergent time intervals are observed with FGGT-LB that is linear and is around 10% to 12% lesser than DHA and the Fuzzy Q-Learning methods respectively as depicted in fig-1.

Similar performance is envisaged even in terms of call dropping ratio as depicted in figure-2 and the ratios indicate that FGGT-LB is being constant at distinct levels of load observed during vivid time intervals. Also, the average call dropping that is observed for FGGT-LB is in the range of 1.7 to 2.2 percent, while the other models that are chosen for comparison has resulted around 2% to 6 %

The cost of signaling resulted for all the three models are depicted in figure-3, and the simulation results reflect that signaling costs that are observed for FGGT-LB is being minimal and constant, but DHA and Fuzzy

Q-Learning has emphasized on signaling costs that are high at initial levels and has dropped low by the time of completion of simulation process, which is high and unstable that compared to the signaling coast observed for FGGT-LB.

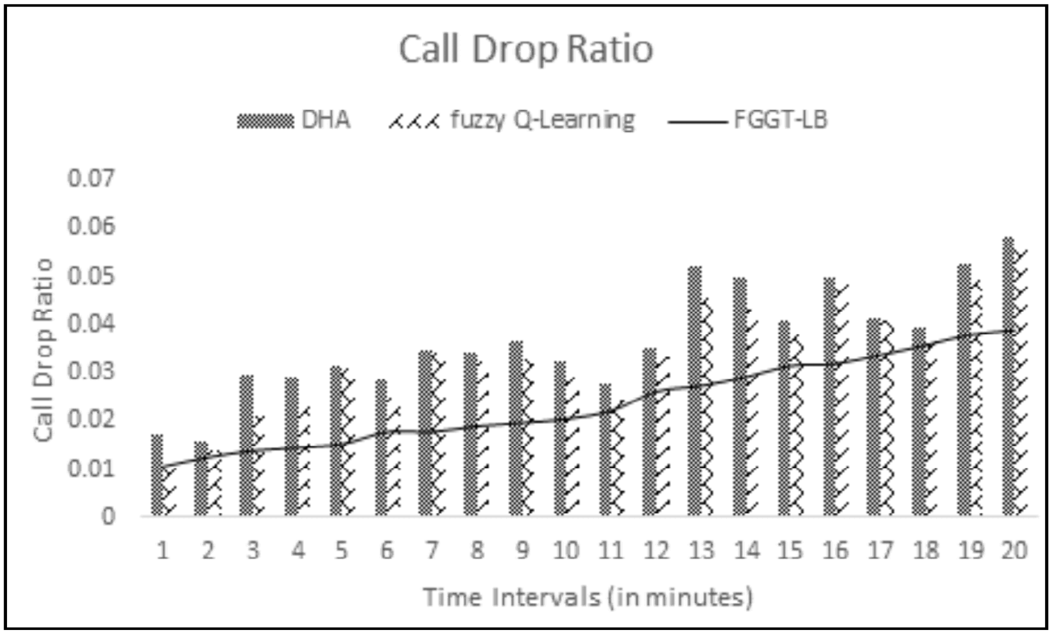

Figure 2: The Call dropping ratio observed at different time intervals

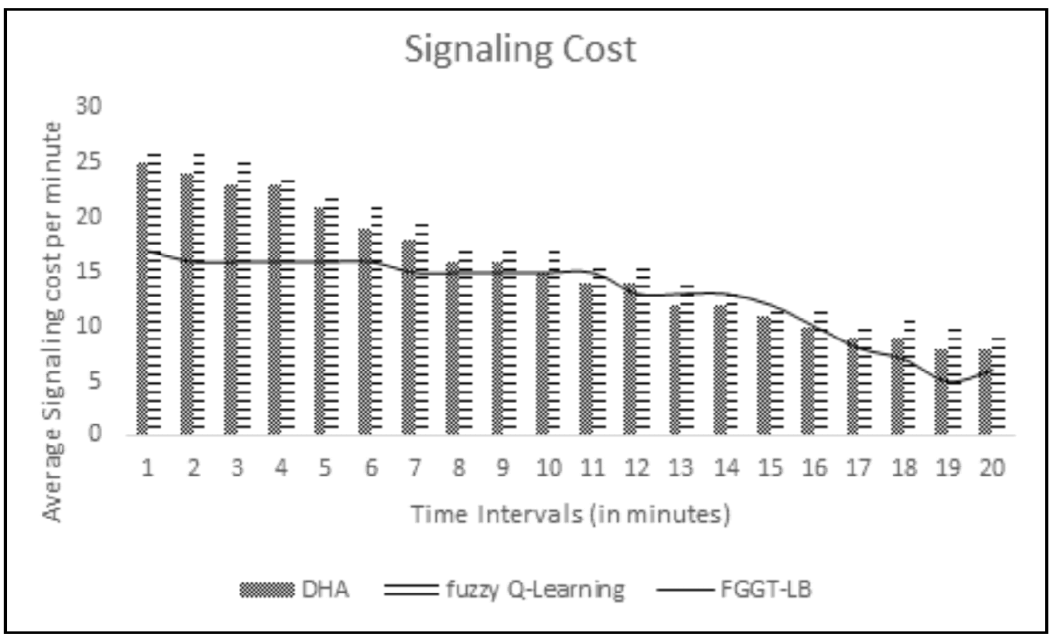

Figure 3: Average signaling costs observed at different time intervals

Quality of Service in the context of handover failures are depicted in figure.4, which denotes that the FGGT-LB comprising minimal handover failures and slightly unstable, but in the instance of DHA and Fuzzy Q-Learning models it has resulted high and unstable failure ratios. Average handover failure observed at varied time intervals are FGGT-LB is around 3.2 % and for FHA and Fuzzy Q-Learning, it is around 8.2% and 6.3% respectively.

In all of the above three models, the ratio of radio link failure is being constantly increased in terms of simulation time intervals, but the failure ratio is being very minimal for FGGT-LB as depicted in figure 5, that is in the range of 0.001 to 0.02 and for DHA it is observed as 0.013 to 0.035 , and Fuzzy Q-Learning as 0.015 to 0.025.

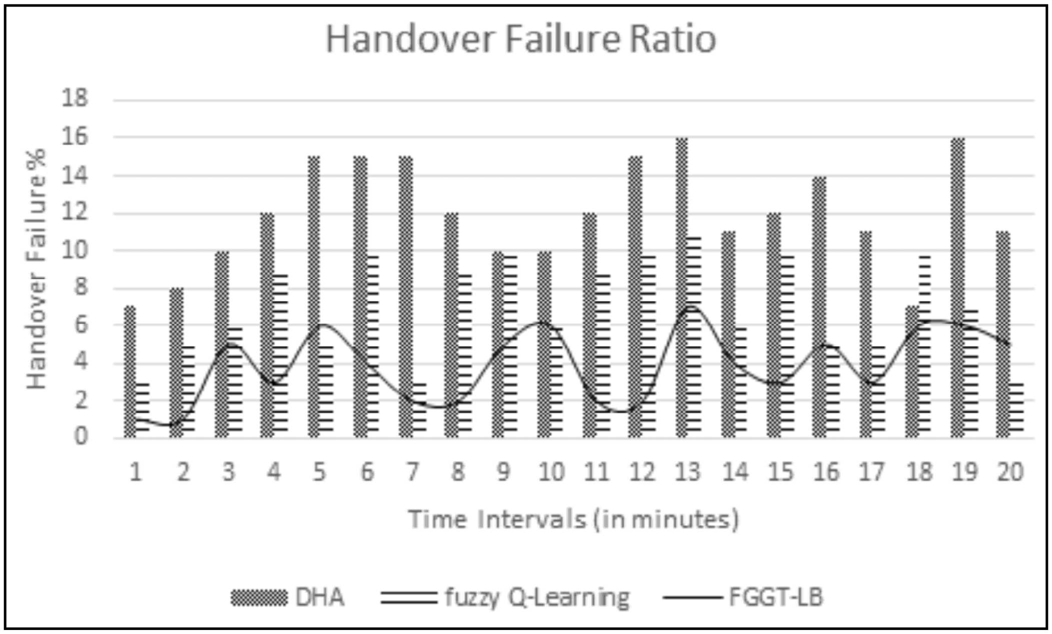

Figure 4: The handover failures observed at different time intervals

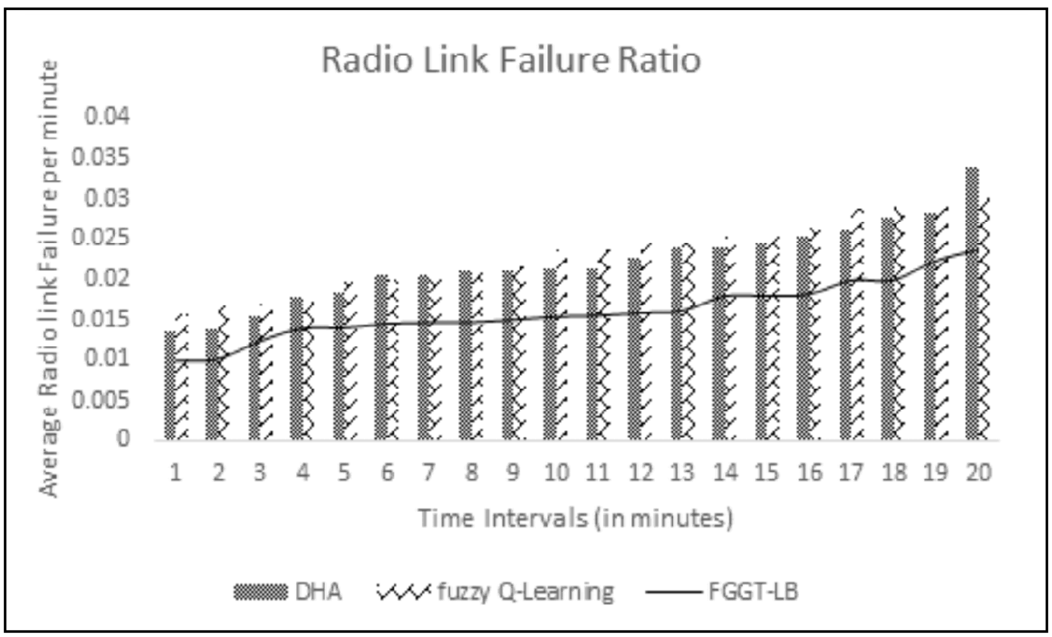

Figure 5: The ratio of radio link failures observed at divergent time intervals

5. CONCLUSION

In this paper, the solution proposed is about adapting the fuzzy guided game theoretic approach for the process of load balancing in LTE networks. In the proposed solution, the load balancing is triggered on the basis of status of every cell, estimated by applying the fuzzy logic. The key metrics like the signaling costs, scope of availability, call blocking and metrics bandwidth are considered for the process. On the basis of cell status, load balancing is triggered using hysteresis adjustments that are carried out dynamically, and is performed relying upon the game theory approach. From the simulation results, it is evident that the proposed solutions minimize the failure of radio links and can support in more efficient performance.

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