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GAME THEORY AND FUZZY BASED LOAD BALANCING TECHNIQUE FOR LTE NETWORKS

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ABSTRACT

In LTE Networks, during load balancing, the adverse effects of radio link failure on the handoff performance are not considered. In order to overcome this issue, in this paper, we propose to design a game theory and fuzzy logic based load balancing technique for LTE networks. In this technique, the load balancing is triggered based on the status of each cell which is estimated using fuzzy logic. Here the metrics call blocking ratio, transmit power, composite available and missing capacity are considered as input for the fuzzy logic and the status of cell is determined as output. Based on the cell status, the load balancing is triggered and the dynamic hysteresis adjustment is performed based on the game theory model. By simulation results, we show that the proposed technique minimizes the radio link failure.

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

1. INTRODUCTION

Long Term Evolution (LTE) standard is made for 4G cellular networks by the 3rd generation partnership project (3GPP). LTE intends at minimizing the system and User Equipment (UE) complications. It allows flexible spectrum deployment in existing or new frequency spectrum and enables co-existence with other 3GPP Radio Access Technologies (RATs).

LTE uses single-carrier frequency division multiple access (SC-FDMA) for the uplink (UL) and orthogonal (OFDMA) in downlink (DL). Hence it provides a flexible and spectrally efficient radio link protocol design with low overhead meeting the challenging targets to ensure good service performance in varying deployments. LTE networks can achieve high spectrum efficiency due to the usage of multi-input and multi-output (MIMO) antenna and orthogonal frequency division multiple (OFDM) technology [1] [3] [5].

1.1 Objectives of LTE

- To minimize the system complexity
- To minimize User Equipment (UE) complexity
- Flexible spectrum deployment [2] [3] [5].

1.2 Need of Load balancing in LTE

The network performance is still influenced by several factors, which creates inter-cell interference (ICI) and load imbalance. So there is a requirement for load balancing in LTE. The basic idea of LB is to free from the excessive traffic from hot spots to neighboring low-load cells. The optimization targets provide a better utilization towards the overall system throughput by providing better QoS to the end users.

A load balancing (LB) scheme is required to minimize the demanded radio resources of the maximum loaded cell to avoid the traffic congestion in long term evolution (LTE) networks. Load imbalance in LTE networks deteriorates the system performance influenced by unbalanced load distribution among nearby cells. Hence the real-time inter-cell optimization adaptable to environment especially when unbalanced and time varying, is needed [3] [5].

1.3 Issues in Load balancing

- Handover
- Consumption of radio resources
- Cell-breathing
- Overlapping area
- Traffic loads
- Load distribution [7] [11] [12]

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1.4 Basics of Game Theory

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

where N = finite set of players

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

UF_i = utility functions.

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

The outcomes are selected by a particular player i with S_i as UF_i and the particular actions selected by other players is S_{-i}.

Rationality is the most basic assumption in game theory. Rational players are assumed to maximize their payoff, which is selfish motivation. In game theory, outcome is the solution of a game. In WSN, intrusion detection system (IDS) acts as one player and intruder plays as opponent player. In the WSN problem, the large WSN is divided into clusters and IDS defends a cluster at any given time, while the attacker disturbs the normal operations.

The main applications of game theory are as follows

1) Decision making in many economic problems especially during bidding.
2) Power control to set the power level of nodes. This is performed to maximize their signal interference to noise ratio (SINR), their selection of path by source node to minimize delay, and their cooperation among the nodes to identify the service and forwarding of the packets to their destination.

1.5 Problem Identification

In load balancing using Fuzzy Q-learning optimization technique [7], the call blocking ratio (CBR) difference and current handoff (HO) margin are considered as input for fuzzy logic and computes the required HO margin as the output.

In [10], the call blocking ratio (CBR) difference and transmitting power (TXP) difference are considered as input for fuzzy logic and computes the required TXP change as the output.

In [11], Composite Available Capacity (CAC) and Composite Missing Capacity (CMC) are considered for triggering the load balancing policy by adjusting the Cell Individual Offset (CIO).

However the load balancing techniques should consider the effects of radio link failure on the handoff performance.

In [4], a dynamic hysteresis adjustment (DHA) is performed based on the handover performance indicator (HPI) which includes radio link failure (RLF) ratio.

In this proposal, we propose to design a game theory and fuzzy logic based load balancing technique for LTE networks.

2. RELATED WORK

LI Bo et al [1] have proposed an inter-domain cooperative traffic balancing scheme focusing on reducing the effective resource cost and mitigating the co-channel interference in multi-domain Het-Net. In the numerical evaluation, the genetic algorithm (GA) as an optimization method is used to demonstrate that the total effective resource cost is significantly reduced through our proposed inter-domain traffic balancing scheme comparing with the intra-domain traffic balancing scheme. The 43% of the resource cost is saved. However the cell-edge throughput and the average cell throughput is not increased effectively.

Zhihang Li et al [2] have proposed an algorithm which includes QoS aware intra- and inter-cell handover and call admission control. Their algorithm can significantly decrease the new call blocking rate for users with QoS requirements and improve the total utility for users without QoS requirements at the cost of a bit degradation of total throughput.

Ahmad Awada et al [3] have presented a game-theoretic analysis for load balancing. Also, they have modeled the utility function maximized by each player and defined the actions leading to the Nash equilibrium point. The load balancing can remarkably increase the capacity usage in the network even when the cells act in a non-cooperative way. If the amount of load to accept or to offload is decided independently by each cell, we would expect that the attained Nash equilibrium point achieves most of the gain intended from load balancing. This indeed paves the way for the possibility of considering the deployment of different load balancing algorithms by various

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manufacturers as the loss in performance would be negligible.

Wenyu LI et al [4] have introduced a dynamic hysteresis-adjusting algorithm in LTE self-organization networks. Furthermore, they take the realistic network situations into account to obtain a more reliable result. The proposed method is evaluated by a series of system-level simulation which witnesses an improvement in handover performance and number of satisfied users in LTE networks.

Omar Altrad et al [6] have proposed a general load-balancing algorithm to help congested cells handle traffic dynamically. The algorithm can be automatically controlled and triggered when needed for any cell on the system. It can be implemented in a distributed or semi-distributed fashion. The triggering cycle for this algorithm is left for the operator to decide on; the underlying variations are slow so there is no need for fast self-optimizing network (SON) algorithms. They apply the load-balancing algorithm to an LTE network and different criteria are adopted to evaluate the algorithm's performance.

P. Muñoz [7] have proposed the optimization of an FLC for load balancing in next generation wireless networks, which is based on dynamically tuning HO margins. Two different optimization approaches using the fuzzy Q-Learning algorithm have been investigated. UEE approach is based on an optimization scheme that explores all the candidate FLC actions throughout the load balancing process. BEE is an optimization scheme that combines both exploitation and exploration to enhance performance while finding the optimal FLC actions and also to provide dynamic adaptation to system variations. The UEE optimization approach is a useful method to accurately preserve the call quality constraint, during the load balancing by simply adjusting a call dropping threshold. However in BEE optimization approach, the FLC would select new optimal actions leading to a lower value of CBR and speeding up the load balancing process while preserving the same constraint in CDR.

WANG Min et al [8] have proposed a min-max load balancing (LB) scheme to minimize the demanded radio resources of the maximum loaded cell. For the mixed multicast and unicast services, multicast services are transmitted by single frequency network (SFN) mode and unicast services are delivered with point-to-point (PTP) mode. The min-max LB takes into account point-to-multipoint (PTM) mode for multicast services and selects the proper transmission mode between SFN and PTM for each multicast service to minimize the demanded radio resources of the maximum loaded cell. The proposed min-max LB scheme requires less radio resources from the maximum loaded cell than SFN mode for all multicast services. However the radio resource consumption increases.

Ming Li et al [9] have proposed an LTE virtualization framework (that enables spectrum sharing) and a dynamic load balancing scheme for multi-eNB and multi-VO (Virtual Operator) systems. They also investigate the parameterization of both schemes, e.g. sharing intervals, LB intervals and safety margins, in order to find the optimal parameter settings. The LTE networks can benefit from both NV and LB techniques.

Pablo Muñoz et al [10] have designed several load balancing techniques based on self-tuning of femtocell parameters. In particular, these techniques are implemented by fuzzy logic controllers (FLC) and fuzzy rule-based reinforcement learning systems (FRLSs). Performance assessment is carried out in a dynamic system-level simulator. The combination of FLC and FRLS produces an increase in performance that is significantly higher than if techniques are implemented alone. Both the response time and the final value of performance indicators are improved.

3. GAME THEORY AND FUZZY BASED LOAD BALANCING TECHNIQUE

3.1 Overview

In this paper, we propose to design a game theory and fuzzy logic based load balancing technique for LTE networks. In this technique, the load balancing is triggered based on the status of each cell which is estimated using fuzzy logic. Here the metrics call blocking ratio, transmit power, composite available and missing capacity are considered as input for the fuzzy logic and the status of cell is determined as output. Based on the cell status, the load balancing is triggered and the dynamic hysteresis adjustment is performed based on the game theory model. Here a utility function is formed in terms of RLF ratio and the hysteresis is dynamically adjusted such that the utility is maximum.

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3.2 Estimation of Metrics

CBR Difference: The Call Blocking Ratio (CBR) is referred as the performed indicator linked to the call accessibility. It is estimated using the following equation (1)

$$\text{CBR} = \frac{z_b}{z_o} = \frac{z_b}{z_b + z_a} \tag{1}$$

Where z_b = number of calls which are blocked by the admission control

z_a = number of calls which are accepted by the admission control

z_o = number of offered calls

CBR difference is obtained between the two adjacent cells (i and j) which is used to balance the traffic among the cells.

$$\text{CBR}_{diff}^{ij}(t) = \text{CBR}_i(t) - \text{CBR}_j(t) \tag{2}$$

Transmit Power Difference (P_{tx}) : The deviation in the P_{tx} value is obtained by comparing with reference value as follows:

$$\Delta P_{tx}{}^{i}(t) = P_{txi}(t) - P_{ref}(t) \tag{3}$$

$P_{ref}(t)$ = pre-defined reference power value.

Composite Available and Missing Capacity: The composite available capacity of the cell (C_c) is estimated using the following equation (4)

$$C_c = 100.\left(1 - \frac{\tilde{L}_i(t)}{L_{trg}}\right) \tag{4}$$

where $L_i(t) = \dfrac{q_i(t)}{bw}$

$$\tilde{L}_i(t) = (1-\beta).\tilde{L}_i(t-1) + \beta.L_i(t)$$

where $\tilde{L}_i(t)$ = cell load

$L_i(t)$ = sample value of the load

q_i (t) = amount of occupied resources at the measurement interval t.

bw= total bandwidth of the cell (in terms of physical resource blocks (PRBs)

β = filter memory

L_{trg} = target operational load in terms of resources occupancy

The composite missing capacity (C_m) of the active cell can be estimated using the following equation (5)

$$C_m = 100.\left(1 - \frac{\tilde{L}_i(t) - L_{trg}}{L_{trg}}\right) \tag{5}$$

3.3 Fuzzy based Cell Status Estimation

We can trigger the load balancing based on the status of each cell which is estimated using fuzzy logic. Here the metrics call blocking ratio difference, power difference, composite available and missing capacity (estimated in section 3.2.1 to 3.2.3) are provided as the input to the fuzzy logic model and fuzzy decision rules are formed. Based on the outcome of the rules, the status of cell is decided.

The steps that determine the fuzzy rule based interference are as follows:

- Fuzzification: This involves obtaining the crisp inputs from the selected input variables and estimating the degree to which the inputs belong to each of the suitable fuzzy set.
- Rule Evaluation: The fuzzified inputs are taken and applied to the antecedents of the fuzzy rules. It is then applied to the consequent membership function.
- Aggregation of the rule outputs: This involves merging of the output of all rules.
- Defuzzification: The merged output of the aggregate output fuzzy set is the input for the defuzzification process and a single crisp number is obtained as output.

The fuzzy inference system is illustrated using

fig 1.

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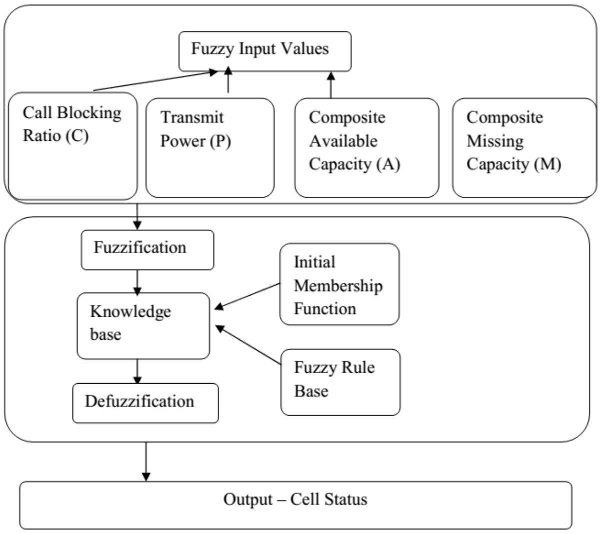

Fig 1 Fuzzy Inference System

Fuzzification: This involves fuzzification of input variables such as Call Blocking Ratio (C), Transmit Power (P), Composite Available Capacity (A) and Composite Missing Capacity (M) (Estimated in section 3.2) and these inputs are given a degree to appropriate fuzzy sets. The crisp inputs are combination of C, P, A and M. We take three possibilities, high, medium and low for C, P, A and M.

Figure 2, 3, 4, 5 and 6 shows the membership function for the input and output variables. Due to the computational efficiency and uncomplicated formulas, the triangulation functions are utilized which are widely utilized in real-time applications. Also a positive impact is offered by this design of membership function.

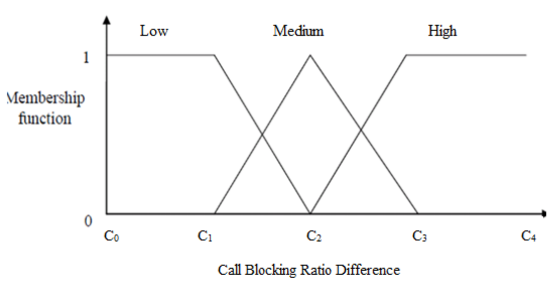

Figure 2 Membership Function Of Call Blocking Ratio Difference

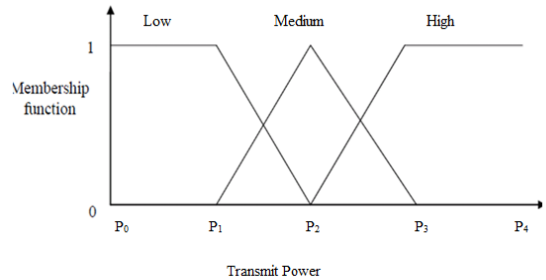

Figure 3 Membership Function Of Transmit Power

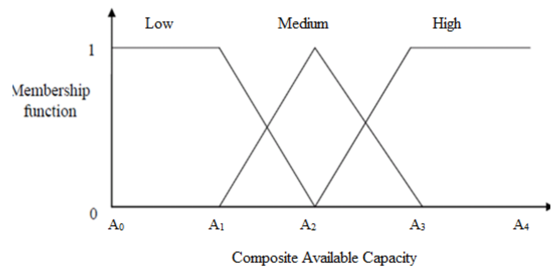

Figure 4 Membership Function Of Composite Available Capacity

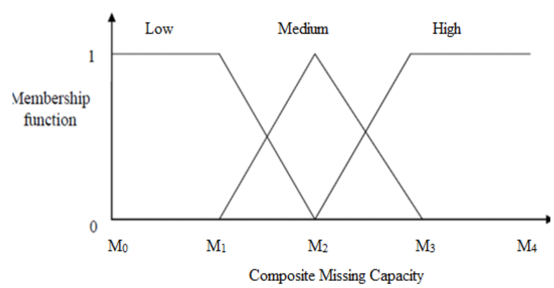

Figure 5 Membership Function Of Composite Missing Capacity

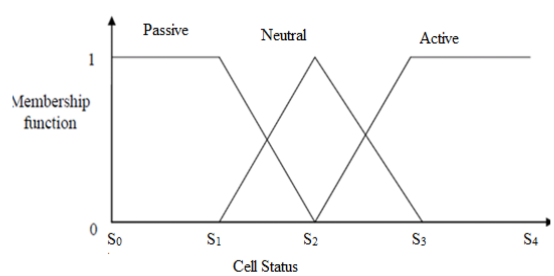

Figure 6 Membership Function Of Cell Status

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In table 2, C, P, A and M are given as inputs and the output represents the Cell Status. (S)

- S_0 to S_1 -> the cell remains in passive status

- The passive cell status reveals that there is minimal load.

- S1 to S_2 - > the cell remains neutral

- The neutral cells does not participate in any load balancing activity

- S_2 to S_3 and above - > the cell becomes active

- The active cell status reveals that there is high load and the cells actively participate in load balancing.

The fuzzy sets are defined with the combinations presented in table 2.

S. No	Call Blocking Ratio Difference (C)	Transmit Power (P)	Composite Available Capacity (A)	Composite Missing Capacity (M)	Cell Status (S)
1	Low	Low	Low	Low	S_0
2	Low	Low	Low	High	S_0
3	Low	Low	High	Low	S_0
4	Low	Low	High	High	S_1
5	Low	High	Low	Low	S_3
6	Low	High	Low	High	S_2
7	Low	High	High	Low	S_4
8	Low	High	High	High	S_2
9	High	Low	Low	Low	S_2
10	High	Low	Low	High	S_2
11	High	Low	High	Low	S_3
12	High	Low	High	High	S_2
13	High	High	Low	Low	S_3
14	High	High	Low	High	S_2
15	High	High	High	Low	S_3
16	High	High	High	High	S_3

Table 2 demonstrates the designed fuzzy inference system. This illustrates the function of the inference engine and method by which the outputs of each rule are combined to generate the fuzzy decision.

For example

Let us consider Rule 7

If (C = Low, P & A = High, M = Low)

Then

Status of Cell is Active (S_4)

End if

Defuzzification: The technique by which a crisp values is extracted from a fuzzy set as a representation value is referred to as defuzzification. The centroid of area scheme is taken into consideration for defuzzification during fuzzy decision making process. The formula (6) describes the defuzzifier method.

$$\text{Fuzzy cost} = \left[\sum_{allrules} f_i * \psi(f_i)\right] / \left[\sum_{allrules} \psi(f_i)\right] \quad (6)$$

Where fuzzy cost is used to specify the degree of decision making, f_i is the fuzzy all rules, and variable and $\psi(f_i)$ is its membership function. The output of the fuzzy cost function is modified to crisp value as per this defuzzification method.

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3.4 Game Theory Based Load Balancing Technique

Based on the cell status (estimated in section 3.3), the load balancing is triggered and the dynamic hysteresis adjustment is performed based on the game theory model. Here a utility function is formed in terms of Radio Link Failure (RLF) ratio and the hysteresis is dynamically adjusted such that the utility is maximum.

The game theory based load balancing technique is modeled by defining the players, the utility function and the possible strategies.

Let N_1 be the active cell which has excess load.

Let N_2 be the passive cell which has minimum load

Let a_1 be the lowest level at which radio link failure 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 opposite location and ready for gaming. It involves the 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) represents decrease in RLF ratio when compared to last adjustment.

The condition (1) represents increase in RLF ratio when compared to last adjustment.

s represents the iterative adjustment

4. The 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 $UF_i \geq 0$ is defined using following equation

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

where A_j = approximation value of the RLF ratio

z_i = number of active cells.

5. Based on value of a_1, N_2 performs the load balancing.
6. The utility function of the N_2 with $UF_0 > 0$ users and a_1>1 is estimated using the following equation

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

Since the network load is already defined, N_2 easily selects a_2 which maximizes the utility function by adjusting the hysteresis value.

4. SIMULATION RESULTS

4.1 Simulation Parameters

We use NS2 [12] to simulate our proposed Game Theory and Fuzzy Based Load Balancing Technique (GFLBT) protocol (FLB, GLB). In our simulation, the packet sending rate is varied as 1, 1.5, 2, 2.5 and 3Mb. The area size is 1200 meter x 1200 meter square region for 50 seconds

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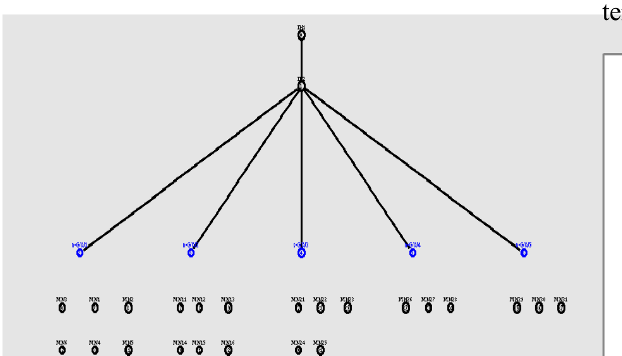
simulation time. The simulated traffic is Video and Exponential (Exp).

Our simulation settings and parameters are summarized in table 1

Table 1: Simulation Parameters

No. of Nodes	31
Area	1200 X 1200
Simulation Time	50 sec
Traffic Source	Video and Exp
Rate	1,1.5,2,2.5 and 3Mb
Propagation	Two Ray Ground
Antenna	Omni Antenna
Initial Energy	4.1J
Transmission Power	0.660
Receiving Power	0.695



Simulation Topology

4.2 Performance Metrics

We evaluate performance of the new protocol mainly according to the following parameters.

Average Packet Delivery Ratio: It is the ratio of the number of packets received successfully and the total number of packets transmitted.

Average end-to-end delay: The end-to-end-delay is averaged over all surviving data packets from the sources to the destinations.

Throughput: The throughput is the amount of data that can be sent from the sources to the destination.

Bandwidth: It is the number of mega bits received by the receiver.

4.3 Results & Analysis

The simulation results are presented in the next section.

Comparison of FLBT and GFLBT: To analyze the performance load balancing technique by using fuzzy logic and without using game theory, In this section, the proposed Game theory and Fuzzy based Load Balancing Technique (GFLBT) is compared with Fuzzy based Load Balancing Technique (FLBT).

We vary the data sending rate as 1, 1.5, 2, 2.5 and 3Mb for Exponential and video traffics

Figure 7 and 8 show the results of bandwidth and fairness for FLBT and GFLBT techniques by varying the rate of Exponential traffic. When comparing the performance of the two protocols, we infer that FLBT outperforms GLBT by 20% in terms of bandwidth and 14% in terms of fairness.

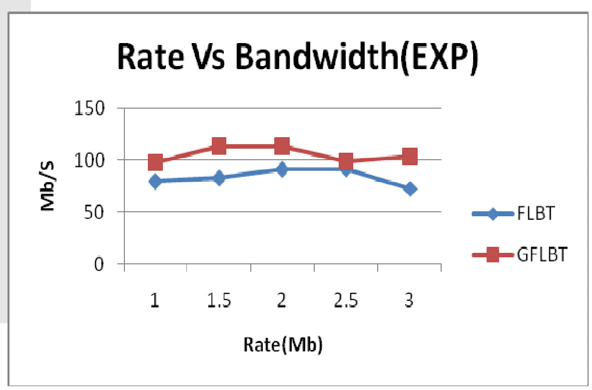


Fig 7: Rate Vs Bandwidth For EXP

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

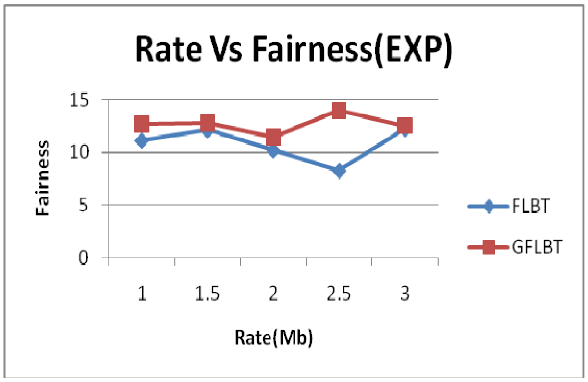


Fig 8: Rate Vs Fairness For EXP

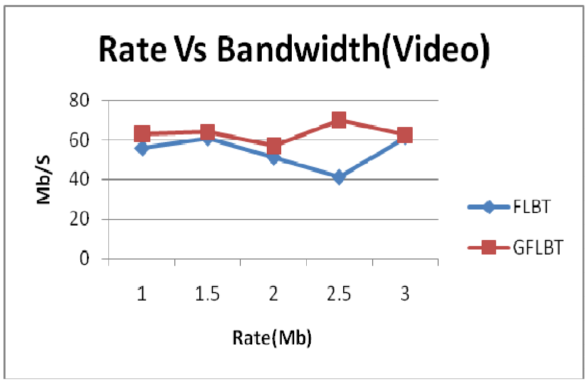


Fig 9: Rate Vs Bandwidth For Video

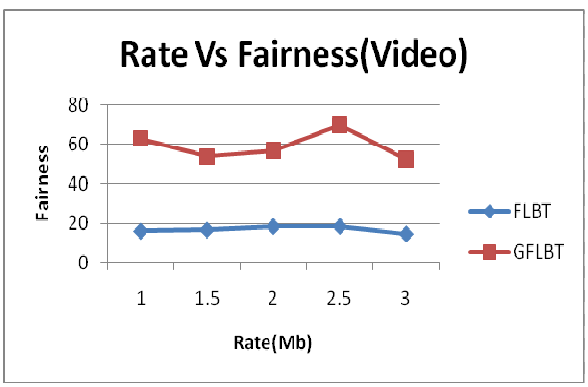


Fig 10: Rate Vs Fairness For Video

Figure 9 and 10 show the results of bandwidth and fairness for FLBT and GFLBT techniques by varying the rate of video traffic. When comparing the performance of the two protocols, we infer that FLBT outperforms GLBT by 28% in terms of bandwidth and 78% in terms of fairness.

Comparison of GLBT and GFLBT: To analyze the performance load balancing technique by using game theory model and without using fuzzy logic, In this section, the proposed GFLBT is compared with Game theory based Load Balancing Technique (GLBT).

The data rate is varied as 1, 1.5, 2, 2.5 and 3Mb for Exponential and Video traffic.

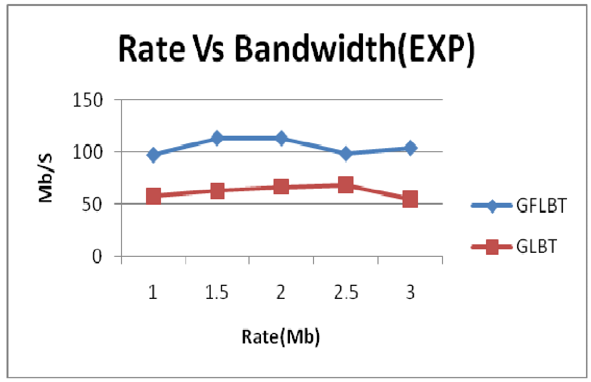


Fig 11: Rate Vs Bandwidth For EXP

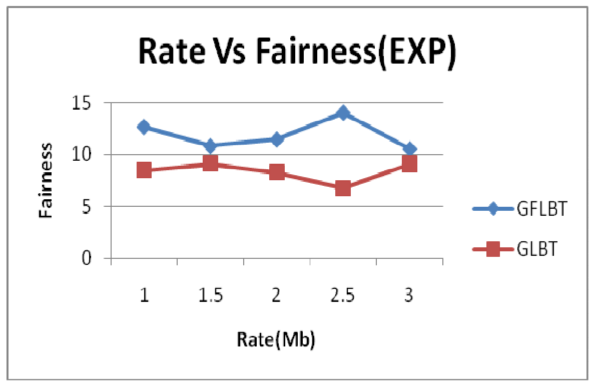


Fig 12: Rate Vs Fairness for EXP

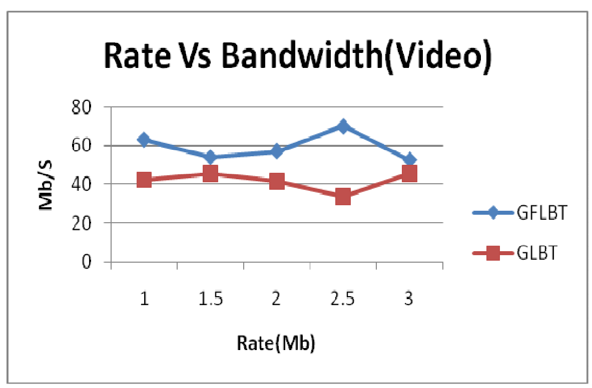


Fig 13: Rate Vs Bandwidth For Video

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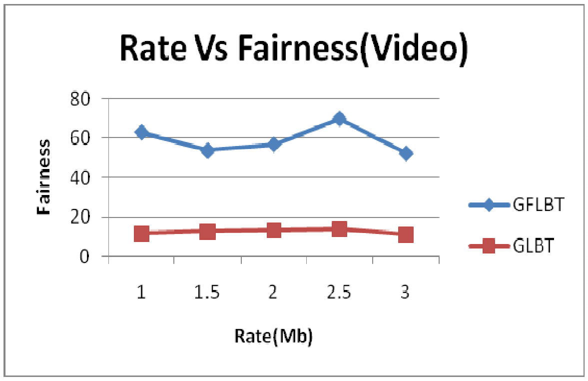

Fig 14: Rate Vs Fairness For Video

Figure 11 and 12 show the results of bandwidth and fairness for GFLBT and GLBT techniques by varying the rate of Exponential traffic. When comparing the performance of the two protocols, we infer that GFLBT outperforms GLBT by 41% in terrms of bandwidth and 28% in terms of fairness.

Figure 13 and 14 show the results of bandwidth and fairness for GFLBT and GLBT techniques by varying the rate of video traffic. When comparing the performance of the two protocols, we infer that FLBT outperforms GLBT by 28% in terrms of bandwidth and 78% in terms of fairness.

Comparison of DHA and GFLBT: In this section, we compare the dynamic hysteresis adjustment (DHA) [4] protocol with the proposed GFLBT protocol. The performance is measured by varying the rate for both Exponential and Video traffic.

Case-1 Exponential Traffic

The data sending rate is varied as 1, 1.5, 2, 2.5 and 3Mb for Exponential traffic.

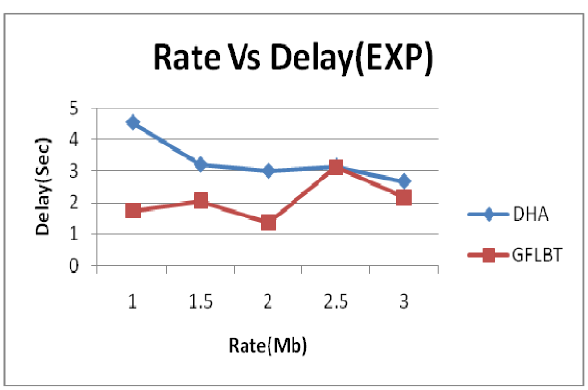

Fig 15: Rate Vs Delay

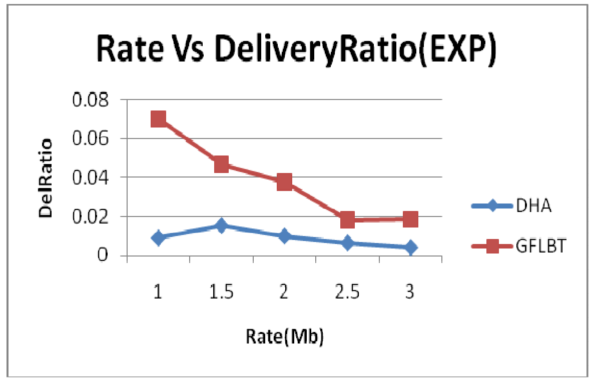

Fig 16: Rate Vs Delviery Ratio

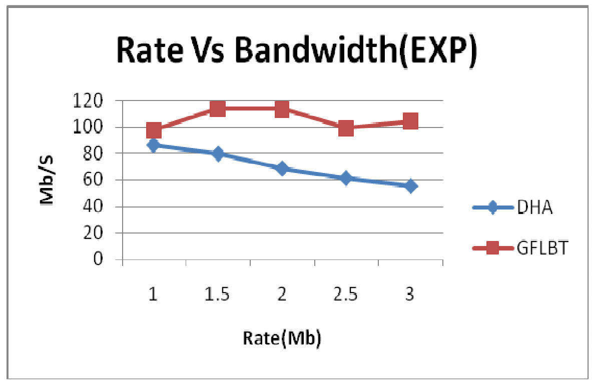

Fig 17: Rate Vs Bandwidth

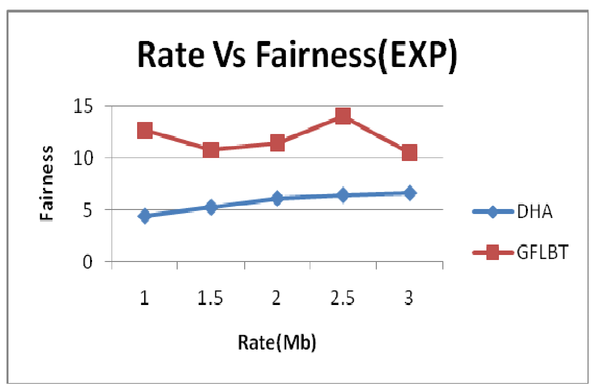

Fig 18: Rate Vs Fairness

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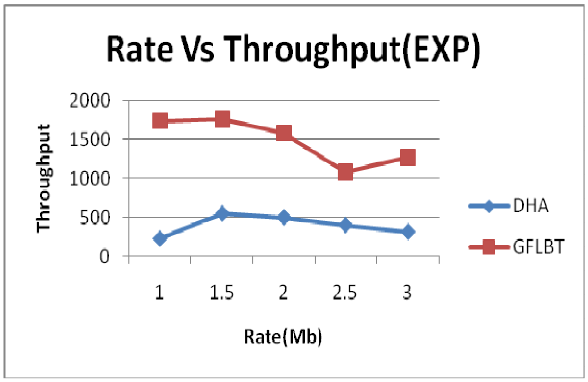

Fig 19: Rate Vs Throughput

Figures 15 to 19 show the results of delay, delivery ratio, bandwidth, fairness and throughput by varying the rate from1Mb to 3Mb for the Exponential traffic in GFLBT and DHA protocols. When comparing the performance of the two protocols, we infer that GFLBT outperforms DHA by 34% in terms of delay, 73% in terms of delivery ratio, 33% in terms of bandwidth, 51% in terms of fairness and 72% in terms of throughput.

Case-2 Video Traffic

The data sending rate is varied as 1, 1.5, 2, 2.5 and 3Mb for Video traffic.

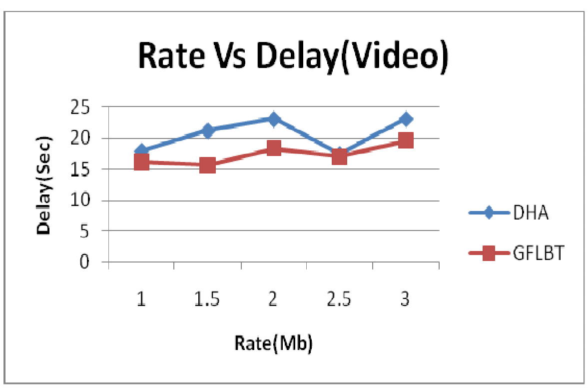

Fig 20: Rate Vs Delay

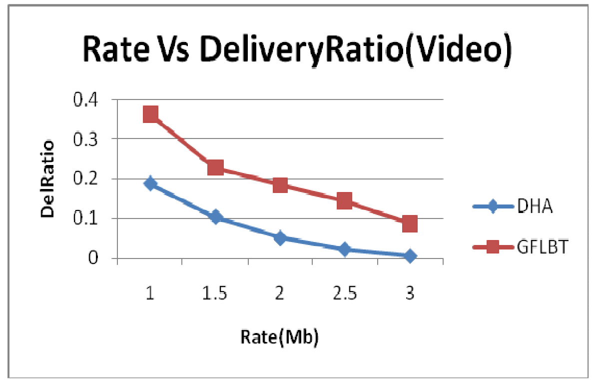

Fig 21: Rate Vs Delviery Ratio

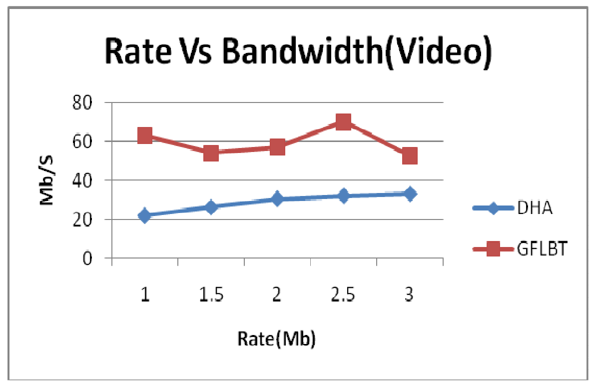

Fig 22: Rate Vs Bandwidth

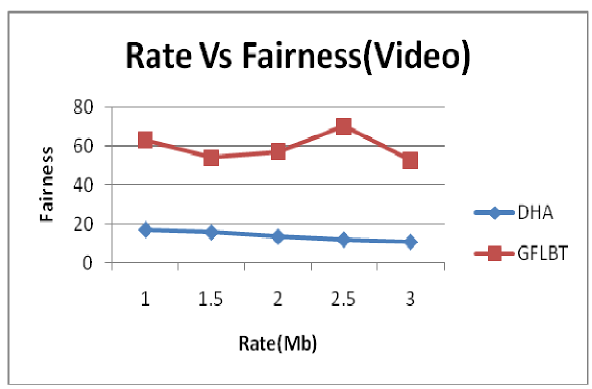

Fig 24: Rate Vs Fairness

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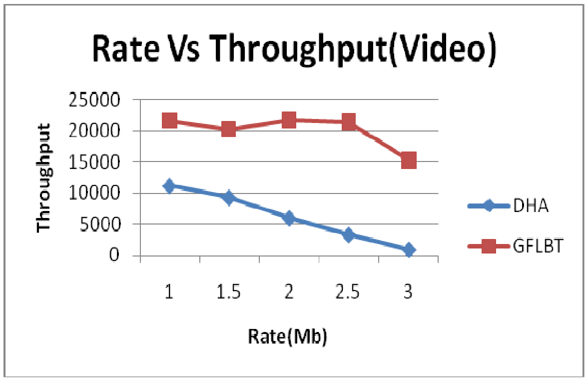

Fig 25: Rate Vs Throughput

Figures 20 to 25 show the results of delay, delivery ratio, bandwidth, fairness and throughput by varying the rate from1Mb to 3Mb for the Exponential traffic in GFLBT and DHA protocols. When comparing the performance of the two protocols, we infer that GFLBT outperforms DHA by 15% in terms of delay, 71% in terms of delivery ratio, 51% in terms of bandwidth, 76% in terms of fairness and 71% in terms of throughput.

5. CONCLUSION

In this paper, we have proposed to design a game theory and fuzzy logic based load balancing technique for LTE networks. In this technique, the load balancing is triggered based on the status of each cell which is estimated using fuzzy logic. Here the metrics call blocking ratio, transmit power, composite available and missing capacity are considered as input for the fuzzy logic and the status of cell is determined as output. Based on the cell status, the load balancing is triggered and the dynamic hysteresis adjustment is performed based on the game theory model. By simulation results, we have shown that the proposed technique minimizes the radio link failure.

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