International Journal of Computer and Information Technology (ISSN: 2279 – 0764)
Volume 13– Issue 3, September 2024

Optimized Q-Learning-Based Handover Decision Algorithm for Femtocells Using Load Balancing in LTE-A Networks

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*Abstract***— The rapid growth of mobile devices and demand for mobile data have made maintaining capacity, high coverage, and data speed challenging. With the emergence of small cell networks, the Long-Term Evolution (LTE) system helped to address these issues, Femtocell technology is being deployed to provide improved indoor coverage. However, a major challenge is the frequent handover and unequal distribution of cell loads, which lead to a reduction in call and data rates. Small cells have changing and unplanned load distribution over time, resulting in certain cells suffering high user density and strong resource competition, while others have low user density and wasteful resources due to low consumption. This imbalance in cell load distribution greatly influences overall network performance and prevents Femtocells from realizing their full potential. Despite several efforts by researchers to enhance network communication, handover is still a challenging issue, many related works have been done in the field but still it needs improvement. This research proposes an Optimized Q-learning-based Handover Decision Algorithm for Femtocells using Load Balancing in LTE-A Networks to improve overall network performance. The algorithm learns to prioritize and select cells with low load during target cell selection and not only provides good Quality of Service (QoS) but also has a low load, resulting in better traffic distribution across the cells. Several simulations were performed using LTE-Sim. Results proved the outperformance of the proposed algorithm over the existing algorithm in terms of QoS with a packet loss ratio for CBR packet transmission of 512 bytes with a rate of 8 packets/second intervals, 88.53%, and VoIP packet transmission of 32 bytes per 20 ms/time interval, 89.24% respectively.**

Keywords- lte-a; q-learning; load balancing; macrocell; femtocell; cbr; voip

I. INTRODUCTION

Cell handover has been considered one of the most challenging issues in the Long-Term Evolution-Advanced (LTE-A) Macrocell-Femtocell network [1], [2]. The exponentially increased evolution of cellular systems from 3G, 4G LTE to the future 5G, and the high increase of end-user items, such as Handsets, Tablets, Laptops, and Machine-to-Machine (M2M) nodes has become a major generator of mobile data traffic, which led to a reduction in signal quality for indoor users, and it requires tens of thousands of Base Stations (BSs) that are densely deployed in a variety of sizes and capacities to provide high coverage and mobility of connectivity [4], [5]. A new technology called Femtocell has emerged, its main purpose is to increase indoor coverage for mobile communication at high speed [6].

Research Project groups like the 3rd Generation Partnership Project (3GPP) are of high interest in trying to reduce the data traffic from Macrocells which will provide relief to both operators and users [7]. There has been a high increase in mobile data users over the last few years and it is still increasing day by day [8]. To cope with such an increased number of users, there is an immense need for a high-speed network because the existing network cannot support such a huge number of users. New network topologies are required that can efficiently accommodate mobile users [9]. There exist different approaches to tackle this challenging issue of a huge number of users and indoor coverage, these include improvement in the formats of transmitting signals and bringing the transmitter and receiver close to each other. Both of these approaches were costly for the operators and hence discarded. Another approach is to introduce small cells within the coverage area of Macrocells.

Femtocell is one of the small cells that is the best solution for offloading the traffic from Macrocell and also for improving indoor network coverage. Its deployment is also economical for the operators, due to the small coverage area from 10m to 100m, the frequency reuse approach is used effectively [10]. Also, Femtocell technology is of high interest for mobile operators to extend the cell phone coverage range, providing high-quality and high bit-rate services for indoor users, and supporting the increasing demand for data traffic in wireless networks [11]. Compared to Microcells and Picocells, Femtocells are deployed in indoor environments such as homes, offices, shopping malls airports, etc. to extend the coverage and improve the capacity of a mobile network [12]. The Femtocell access point (FAP) can be classified into two types depending on the capacity and number of users. They are classified as home FAP which can support three (3) to five (5) users and enterprise FAP which can support eight (8) to sixteen (16) users [4]. The Femtocell operates in a licensed spectrum and communicates with the operator's network over a broadband connection such as a Digital Subscriber Line (DSL) and cable modem [11]. Also, Femtocells are operated with low transmission power (maximum of 20dBm) and this transmitted signal power defines the Femtocell coverage area [13].

There are many advantages to the deployment of Femtocells to both users and mobile network operators. For the users, the use of a Femtocell within the home enables far better coverage and capacity to be enjoyed, and the battery life of User Equipment (UE) is also improved because of the low power radiation [8]. For the network operators, the cost of deploying extra infrastructure to increase capacity is substantially reduced, as there is no added cost in maintaining and running the Femtocells. It simply provides a cost-effective means of improving capacity and Macrocell reliability. Despite these advantages of Femtocell technology, there are challenges associated with its deployment. These include interference management, resource allocation, and seamless handover [14].

In mobile communication, the Handover (HO) technique can be viewed as allowing the connected User Equipment (UE's) with Evolved Node-B (eNB) or Home Evolved Node Base (HeNB), to be handed off to the next HeNB without any disconnection [15].

To ensure equal resource utilization across all cells, load balancing is used to address the uneven distribution of traffic load across multiple cells. There will be a high QoS in all cells and for all users if resources are used equally. Since a small number of UEs are associated with small cells due to their low transmit power in comparison to Macrocell, load balancing is a significant problem in LTE networks. A low load in Femtocells and a high load in Macrocells will result from this [16].

II. Literature Review

[17] Provide a unique technique for load balancing and resource allocation in the O-RAN system, employing reinforcement learning to dynamically distribute resources among multiple base stations. Simulations test the proposed algorithm's performance, indicating it produces a considerable increase in network throughput and fairness [17]. However, the performance may be influenced by network conditions, such as heavy interference or congestion.

[18] Consequently, HO is one of the main aspects of HSTs to guarantee the seamless connectivity and communication of served UEs inside train carriages. In fact, in a high-speed moving CCMF environment, HO can occur more frequently, therefore, providing an effective HO procedure to mitigate the outage and dropping call probabilities were the main targets of this work. The proposed HO procedure considered the process of handing over the MF itself from one DeNB to another accompanied by a group UEs HO for all attached UEs to the serving MF. The achieved results showed a reduction in the outage and dropping call probabilities of the proposed HO scheme compared to the conventional HO scheme [18]. However, the work concentrates on dropping call probability to reduce the HO schemes, there is a need to further improve the Quality-of-service parameters as well as the energy consumption.

[19] In this paper, it was found that most handover decision algorithms handled only one Femtocell one Macrocell scenario after looking at a wide spectrum of handover decision algorithms. In light of the current heavy and haphazard Femtocell deployment, this scenario is not plausible. The new decision algorithm that has been developed to address the difficulties raised above, including energy inefficiency, is the primary benefit of this paper. The proposed algorithm handles handovers of UEs that are members of the CSG and those that are not. Additionally, it addresses the problem of cell search by combining CSG and NCL. For UEs at medium and high mobility, the adoption of a time to trigger with a parameter of 5 seconds has been found to have a massive decrease in the occurrence of duplicated handovers enabling the Advanced LTE system's energy efficiency to be improved, even though not all segments were simulated. Since RLF was reduced, the needless handover ratio decreased by almost 10%, and the installation of TTT boosted system energy efficiency by 30% [19]. However, further research can be carried out to improve the quality-of-service parameters, such as Throughput, End-to-End Delay, Packet Delivery ratio, and Packet Drop as well as Energy consumption.

[20] Present a new load-balancing approach based on deep reinforcement learning. The approach utilizes a Double Deep Q-Network (DDQN) to control two parameters: Cell Individual Offset (CIO) and eNodeBs' transmission power. By adjusting these parameters, the proposed model aims to achieve better load distribution in the network. The results demonstrate that the proposed approach improves the network's overall throughput by up to 21.4% compared to a baseline scheme and by 6.5% compared to a scheme that only adapts CIOs [20]. However, The Authors briefly mention existing load-balancing algorithms that rely on CIO adjustment but do not consider neighboring eNodeB utilization.

[21] The system performance obtained from the proposed scheme indicates a lower percentage of control signaling rate and Packet Loss Ratio compared to the benchmarks used for this algorithm. The simulation results indicate that the suggested scheme based on the Q-learning methodology can help to improve the handover stage in LTE-A systems [21]. However, choosing appropriate factors to enhance the cell selection stage is still a challenge. Further work is to be designed and implemented in this field, including load balancing, hybrid Femtocell schemes, and UE velocity.

[15] In this paper, the simulation result shows up some advantages of the new proposed HO mechanism as eliminating the unnecessary HO and ensuring the load balance of the target FAP and the entire network. Also, the serving cell takes into consideration the real capacity of the available survived target FAP. Note that, if the target FAP has a heavy UE capacity state around the threshold, the serving FAP will give up and will choose the next lighter load cell for the HO process. Finally, this mechanism can lighten the over-charge of resource usage by using the BW resources of selected target FAP only. The results demonstrate that using the proposed scheme to predict the best target FAP for HO, causes a better performance compared to the traditional procedure. Also, it improves the QoS in the entire network by decreasing the failure probability rate and reducing the effect of ping-pong at an almost stable level [15]. However, if the target FAP has a heavy UE capacity state around the threshold, the serving FAP will give up and will choose the next lighter load cell for the HO process, which further introduces a delay to the network as well as energy wastage due to time it takes before selection between lighter load and heavy.

[22] This paper analyzed the handover performance in the Femtocell network by using two types of handover algorithms which are the standard A2-A4-RSRQ handover algorithm and the proposed prediction handover algorithm. The experiments were used to analyze the handover performance in terms of the number of handovers and the user throughput. The results show that predicting the best target cell and the best time for handover causes a better performance to compare if only relying on RSRQ value. The experiments also analyze the root cause of user throughput degradation [22]. Nevertheless, there is a need for further improvement on the aspect of mobility management in the Femtocell network and examining the interference level as well as energy consumption.

[23] Introduced a handover algorithm based on calculating the equivalent received signal strength and dynamic margin. The algorithm determines when a handover from Macrocell to Femtocell or vice versa should occur based on these metrics. The results show improvements in two major performance parameters: reduction in unnecessary handovers and Packet Loss Ratio. The proposed algorithm achieves a reduction of 55.27% and 23.03% in Packet Loss Ratio and a reduction of 61.85% and 36.78% in unnecessary handovers at speeds of 120 km/h and 30 km/h, respectively. [23]. However, this research does not explicitly address the algorithm's scalability and robustness in large-scale networks or the presence of dynamic network conditions. As the number of femtocells and mobile devices increases, the algorithm's efficiency and ability to handle network dynamics should be thoroughly investigated.

[24] In this research work, an enhanced handover algorithm has been proposed for Macrocell to femtocell handover. Specifically, the algorithm takes into consideration the speed of the user as well as the signal level of the user to the Femtocells before making the handover decision. Calls from the high-speed users are made to connect to the Macrocell whereas calls from the low-speed users were connected to the Femtocell. In addition, the potential Femtocells have been listed, and the algorithm further checks for the target Femtocell that can accommodate new users [24]. However, there is a need to determine the effect of the call admission control scheme on both the call blocking and call dropping probability as well as improvement in the quality-of-service parameters.

[25] In this paper, the authors proposed a new algorithm to minimize the target FAPs and reduce the number of handovers by choosing the best target FAP among the neighbor FAPs list. During the handover procedure, the researchers choose the target FAP with optimum RSSI value and optimum Cell Load to avoid handover failure and frequent subsequent handovers. The handover takes place specifically to a UE as identified in the FAP's list [25]. Despite that, there is a need for extra processing than the formal handover and also Femto should maintain a separate table for each UE attached to it, also it can be modified to maintain a unified table for all the UEs attached to the Femto.

[26] The LTE integrated system is the optimal solution for the upcoming mobile networks, the mobility management of Femtocellular with Macrocellular networks presents an important part of the effective deployment of the Femtocell technology, offering LTE integrated system seamless and fast handover, minimizing unnecessary handover, and a minimum number of signaling during handover. [26]. However, there are still hard technical challenges to be studied as the optimization of the handover and interference management, extends the time spent by users attached to the Femtocells, also the whole solution for the mobility management in integrated systems is not considered.

[8] In this paper, the researchers addressed the challenge of handover in an LTE Macrocell-Femtocell network consisting of one Macrocell and open-access Femtocells. A new Femtocell-to-Femtocell handover decision algorithm based on the UE's velocity and the RSS which selects an appropriate target Femtocell among many possible candidates is proposed. The proposed scheme reduces the number of handovers by increasing the time interval between handover triggers during a call connection. To avoid unnecessary handovers initiated by high-velocity users, the algorithm hands over these users to the microcell [8].

[27] Offer a Q-learning-based handover (HO) method for high-speed railway (HSR) wireless communications. The proposed approach leverages Q-learning algorithms to optimize HO choices and decrease superfluous HOs, which enhances network performance. The suggested method addresses the movement of the HSR and applies to a dense 5G HSR deployment [27]. However, the performance of the method largely depends on the correctness of the channel model utilized. The algorithm only considers four parameters (HO cost, SINR, RSRP, and period of stay) as rewards, which may not be adequate to capture all the critical elements that determine the HO choice. The approach is computationally expensive and needs a substantial amount of memory to store the Q-table, which may restrict its applicability in resource-constrained contexts. Also, the time interval between the handover interval that is being increased will cause delay and decrease throughput as well as energy consumption.

[28] In this paper, the authors proposed a SON handover scheme to improve the efficiency of handovers in enterprise Femtocell networks. The proposed SON handover scheme uses UE positions and sub-regional information inside the building to intelligently reduce unnecessary handovers. In comparison with the [28] scheme, the proposed algorithm shows an

improvement of 2% in the throughput of UEs. [28]. However, the research work focused on throughput only, there is a need to consider the load balancing factor for handover decisions and achieving energy efficiency in UE during handovers

[29] In this paper, the researchers proposed a new handover decision algorithm based on the prediction of the mobile user position in a two-tier Macro/Femto environment. Specifically, the researchers exploited the predicted direction of the mobile user to identify a list of FAPs candidates that are most likely to be visited. The research shows an improvement over the traditional on the aspect of Drop rate and signal strength [29]. However, the research did not take into account the FAP's power, which might cause another handover or even degrade the performance of the network by introducing packet drop into the network which might lead to low throughput as well as packet delivery ratio.

[30] This research paper proposed a machine learning algorithm to improve handover performance between indoor Femtocells and external Macrocells for LTE. Based on experience, the algorithm builds a representation of the radio environment and seeks to suppress handover in regions where unnecessary handover has been executed previously. The algorithm, which runs on the Femtocell base station, requires no prior knowledge of the architecture of the building in which it is deployed; thus, it is fully consistent with the SON plug-and-play requirement. It is demonstrated that the algorithm can reduce unnecessary handover by up to 70% [30]. However, there is a need to consider optimal tuning of the TTT and handover parameters in situations where handover is deemed necessary. As part of this investigation, the effects of external interference and the impact on Macrocellular load are supposed to be considered to support the analysis of call drop rates.

[31] In this paper, a revised signaling procedure of handover is presented based on the Home eNodeB GW in Femtocell integrated LTE-Advanced network. A handover algorithm based on the UE’s mobility state has been studied and evaluated in terms of handover signaling. The comparison with the traditional algorithm shows that the algorithms proposed in this research have a better performance in handover signaling overhead, especially for the high proportion of high mobility users scenario [31]. However, the researchers focus on high mobility users only the signaling overhead on lower mobility users degrades the performance parameters as well as energy consumption.

[32] In this paper, we have proposed a HO decision algorithm for the LTE-A Femtocell network, which jointly considers the impact of user mobility, interference, and energy efficiency. The proposed algorithm utilizes standard signaling quality measurements to sustain service continuity and reduce the mean UE transmit power. System-level simulations showed that compared to existing algorithms, the proposed algorithm significantly reduces the interference and energy expenditure [32]. However, the algorithm increases the network's core network signaling, degrading the network performance of delay and throughput.

[33] In this paper, an effective algorithm to reduce unnecessary handovers in an indoor-outdoor scenario has been proposed. This self-optimizing algorithm uses kernel methods and neural networks to improve handover efficiency while retaining the required plug-and-play functionality of SON in LTE systems. By monitoring the location of the user when a handover trigger is made, the Kernel SOM algorithm can be used to analyze the situation and decide whether the mobile user is within a zone where handover should be permitted or prohibited. Within this work, the assumption is made that a mobile user generally will walk past a window and through a door but the Femtocell is given no prior knowledge as to where these locations are within the environment. In a situation where the system has incomplete knowledge about the number of permissive and prohibition zones, the algorithm is still an improvement over a typical LTE system. It may be possible to propose values for k by a cursory survey of the indoor area by noting the number of doors and windows [33]. However, the work was built under the assumption of knowing the k value, which will degrade the throughput of the network, delay as well as energy consumption due to the inaccuracy of knowing the k value.

[34] The authors presented Prefetch-based Fast Handover, a modified handover procedure that aims to tackle the shortcomings in Legacy Handover procedures introduced by an increasing number of Femtocells in modern LTE cellular networks. They focus on fast-moving UEs in the network that may otherwise fail to hand over to quickly passing Femtocells on their path. By enabling such UEs to handover to a larger number of Femtocells, and by speeding the handover process, they allow fast-moving UEs to take maximum advantage of Femtocells in the network, rather than relying mainly on the Macrocell. They make small modifications to the message flow in the Legacy Handover procedure, without making any changes to the system architecture, to achieve this faster and more efficient handover [34]. Despite that, the algorithm is at the cost of higher consumption of wireline network resources. Due to the concentration of the higher-moving UEs, also the algorithm works well on fast-moving rather than slow-moving UEs.

[35] proposed a modification of the adaptive Handover Mechanism (HM) to enable its easy implementation to the networks with Femto Access Points (FAPs). The adaptive HM reduces the number of redundant handovers while keeping the throughput gain of open/hybrid access Femtocells as high as possible. Compared to the former adaptive HM assuming exact knowledge of cell radius and MS-AS distance, the proposed technique needs information neither on the UE location nor on the FAPs positions that cannot be easily obtained. The proposed solution uses either RSSI or CINR ordinarily measured by a UE during the scanning of its neighborhood [35]. Despite the efforts of the researchers in trying to alleviate handover, another issue arises which is the dependency on the RSSI or CINR which might cause energy wastage as well as uncontrollable delay.

III. PROBLEM FORMULATION

In the presence of addressing various issues in network performance such as unnecessary handovers, signaling rate, end-to-end delay, packet drop, packet delivery, load balancing, and throughput, researchers have made significant efforts to identify and fill the existing gaps. Despite these endeavors, certain gaps remained unaddressed.

To ensure equal resource utilization across all cells, load balancing is to be used to address the uneven distribution of traffic load across multiple cells. There will be a high QoS in all cells and for all users if resources are used equally. Since a small number of UEs are associated with small cells due to their low transmit power in comparison to Macrocell, load balancing is a significant problem in LTE networks.

Therefore, the major contribution to this work, is the Optimization of [21], based on the Q-learning Algorithm for load balancing, to improve the performance parameters of packet loss using CBR and VoIP applications.

IV. Statement of the Problem

The growing number of mobile users, along with the need for more reliable and rapid wireless networks, has made it challenging to maintain capacity, high coverage, and data speed. The usage of small cell networks is one feasible approach to address these challenges, specifically Femtocells, which are made up of several types of small cells. However, a crucial difficulty in Femtocells is the unequal distribution of cell loads during cell selection in the handover process which affects the effective use of the network resources.

Small cells have changing and unplanned load distribution over time, resulting in certain cells suffering high user density and strong resource competition, while others suffer from low user density and wasteful resource consumption. This mismatch in cell load distribution has a great influence on overall network performance and prevents Femtocells from realizing their full potential

To address this issue, a load-balancing algorithm that prioritizes cells with low load during target cell selection in the handover process UEs be developed. The algorithm is to improve the usage of small cells by reducing Packet Loss Ratio, while efficiently allocating the load among cells to maximize the benefit of Femtocells.

V. Simulation Analysis

Simulation modeling was used in this research, among the various methods of performance analysis. In this research Network Simulator Version 3.35 (NS3.35) is the simulation environment that was used for the implementation and evaluation of the proposed algorithm. A network Simulator is a discrete event simulator that supports various types of Transfer Control Protocol (TCP), User Datagram Protocol (UDP), and different models of Unicast and Multicast communications, as well as different Multicast protocols. Also, supports mobile networking such as local and satellite networks. However, it supports applications like web caching. Network Simulator (NS) uses Network Animator (NAM), an animation tool, developed in Tcl/Tk, to visualize the simulation packet traces which are created by running Network Simulation (NS) scripts. Network Simulator (NS) and NAM could be used together to demonstrate different networking issues.

VI. Simulation Setup

In this section, simulation setup, and working of the optimized algorithm have been discussed. Network Simulator NS3.35 has been used to test the performance of the proposed algorithm. The simulation used two Macrocells, with gradual numbers of femtocells configured as 30, 50, 70 and 90, a constant UE velocity of 30 kmph and gradual numbers of UEs configured as 15 and 30. A number of simulations were performed to test the performance of the optimized algorithm by changing the number of Femtocells and UEs.

TABLE I. SIMULATION PARAMETERS

Parameters Value	Value
Simulation Area	1000 x 1000m
Macrocell	2
Femtocell	30-90
UE	15-30
Macrocell TX Power	46 dBm
Femtocell TX Power	20 dBm
Bandwidth	25
Threshold	10
UE velocity	30 kmph

VII. Optimized (Q-Learning Algorithm)

TABLE II. LIST OF NOTATIONS

Parameters Value	Value
Q	Quality table
T	Current time step
s	Current state
a	Current action
R	Reward received for taking action a in state s
α	Learning rate
γ	Discount factor
ν	Next state
b	Next action
T	Threshold value
L	Cell Load
P	Priority queues for handover requests

The contribution of this research is based on the Optimization of the Reinforcement Learning Algorithm (Q-Learning Algorithm) to improve the performance parameters, giving more emphasis on Load Balancing which is the gap identified in the research paper [21] and it is incorporated in the previous algorithm as:

- By identifying the Load of each Cell with unequal distribution of traffic load over multiple cells in such a way that there is an even resource utilization in all the cells. Thus, having an even resource utilization, there will be a high QoS in all cells and for all users.
- Ability to prioritize handover with higher load cell over that with lower load during the handover process.

The equation is a recursive formula for updating the Q-table, which stores the expected reward for taking a particular action in a particular state. $Qt\ (s,\ a) = (1 - \alpha)\ Qt{-}1(s,\ a) + \alpha\ (Rt\ (s,\ a) + \gamma maxb\ Qt{-}1(v,\ b))$ Equation

The equation can be broken down into the following steps:

1) $(1 - \alpha)\ Q_{t-1}(s,\ a)$ is the previous estimate of the expected reward for taking action a in state s.

2) $\alpha\ (R_t\ (s,\ a) + \gamma max_b\ Q_{t-1}(v,\ b))$ is the new estimate of the expected reward for taking action a in state s. The new estimate is calculated by multiplying the following factors:

- The α is the learning rate. This controls how much weight is given to the new estimate.
- $R_t\ (s,\ a)$ is the reward received for taking action a in state s.
- γ is the discount factor. This controls how much weight is given to future rewards.
- $max_b\ Q_{t-1}(v,\ b)$ is the maximum expected reward for taking any action in the next state v.

The Q-table is updated using the equation at each time step. As the algorithm progresses, the Q-table will converge to the true expected rewards for all actions in all states.

VIII. RESEARCH FRAMEWORK

The framework of the optimized algorithm is presented in this chapter as a form of chart in Figure 1 the enhancement starts by developing the algorithm, then the algorithm is simulated, and after that, the algorithm is implemented, a decision is made either evaluating the results or modifying the existing algorithm, and then evaluating the results of the algorithm. Finally, validating the algorithm.

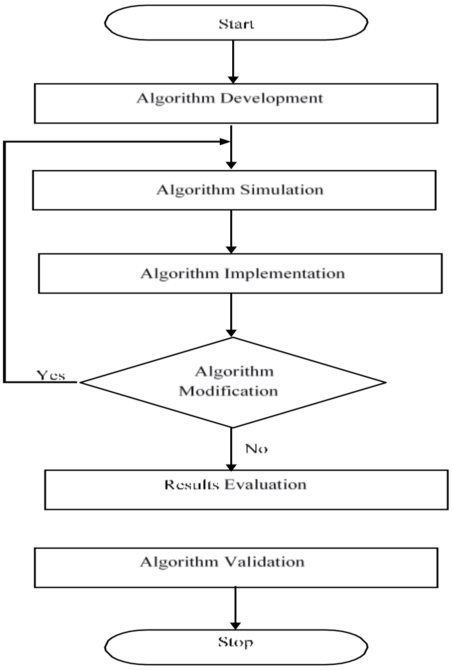

Figure 1. A framework of the enhanced model

IX. DETAILED STATES OF THE PROPOSED ALGORITHM

1) Existing State $_{(s)}$

2) Select an action $_{(a)}$ depending on the decision-selection strategy.

3) If the load of cell $L_{(s)}$ is greater than the threshold $T_{(s)}$, handover the user to the next best cell.

4) Consider load-aware state information and priority queues

5) Execute the selected action and observe the reward (R_t+1), the next state (S_t+1), and the load of the cell $L_{(s)}$.

6) Update the Q-table using the Q-learning update rule, where α is the learning rate and γ is the discount factor.

7) Set the state for the next iteration ($s_t \leftarrow s_t$+1)s.

X. OPTIMIZED ONE TRAIL OF Q-LEARNING PROCESS

***s*:** existing state
***a*:** activity taken depending on the decision selection strategy
***R (s, a)*:** reward as an output of activity (a) in state (s)
***sn*:** upcoming state after executing an activity (a)
$L_{(s)}$: load of cell in state s
$T_{(s)}$: Load threshold for cell in state s
***P*:** priority queues for handover requests based on load conditions
Step 1: set the initial state (s)
Step 2: select an activity (a) depending on the decision selection strategy
Step 3: if L(s) > T(s): handover the user to the next best cell
Step 4: consider load-aware state and priority queues
Step 5: a reward R (s, a) is obtained as a result
Step 6: update $Q_t\ (s,\ a) = (1 - \alpha)\ Q_{t-1}(s,\ a) + \alpha\ (R_t\ (s,\ a) + \gamma max_b\ Q_{t-1}(v,\ b))$
Step 7: $s \leftarrow sn$

By applying Optimized reinforcement learning in LTE Networks using Q-Learning, agents can learn to make optimal decisions to maximize call quality, data transmission rates, and overall network performance. They can adapt their actions based on the rewards received from the environment, leading to improved user experience and efficient utilization of network resources.

XI. RESULTS AND ANALYSIS

The results obtained from the simulation were discussed in this chapter. The following results were based on the packet loss Ratio and Control Signaling Rate of different UE groups using varying numbers of Femtocells.

A. Packet Loss Ratio

Packet loss refers to the ratio of transmitted packets not successfully delivered to the intending receiver or destination. It usually occurs when the sending node is unable to transmit the packet to the intending receiver during the handover process. However, congestion due to a lack of Load Balancing is one of the main reasons for packet loss.

1) CBR Application: Figures 2 and 3 below depict the packet loss concerning change in packet transmission. In the *proposed algorithm Load Balancing was used to avoid the occurrence of congestion, with varying Femtocell density from 30 to 90 cells for each UE group 15 and 30 using the CBR application, packet loss has been remarkably reduced in the Optimized algorithm compared to the existing algorithm, for a CBR packet transmission of 512 bytes with a rate of 8 packets/second intervals.*

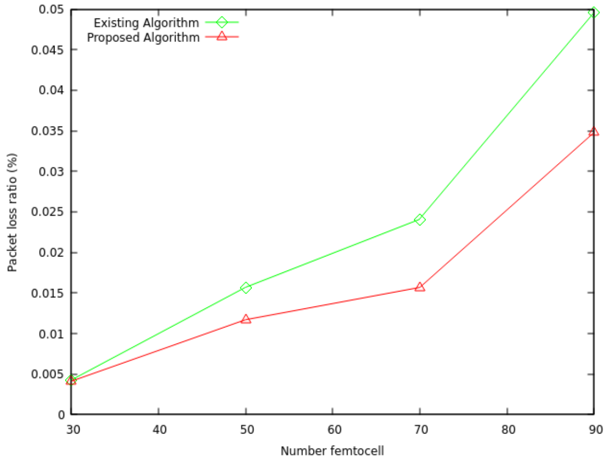

Figure 2. 15 UEs Packet Loss Ratio Comparison using CBR Application

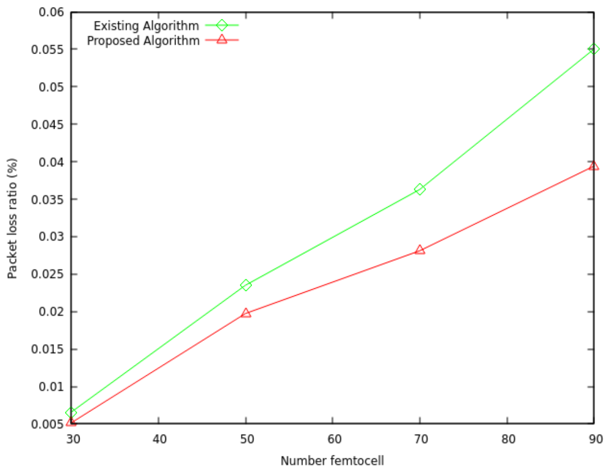

Figure 3. 30 UEs Packet Loss Ratio Comparison using CBR Application

The proposed algorithm reduced the Packet Loss Ratio in comparison to [20] handover for each of both UE groups for each femtocell density using the CBR application. In general, the proposed algorithm with CBR reduced the Packet Loss Ratio by 88.53% compared to [20] handover algorithm in all scenarios.

2) VoIP Application: Figures 4 and 5 below depict the packet loss concerning change in packet transmission. In the proposed algorithm Load Balancing was used to avoid the occurrence of congestion, with varying Femtocell density from 30 to 90 cells for eachUE group 15 and 30 using the VoIP applications, packet loss has been remarkably reduced in the Optimized algorithm compared to the existing algorithm, for a VoIP packet transmission of 32 bytes per 20 ms/time interval.

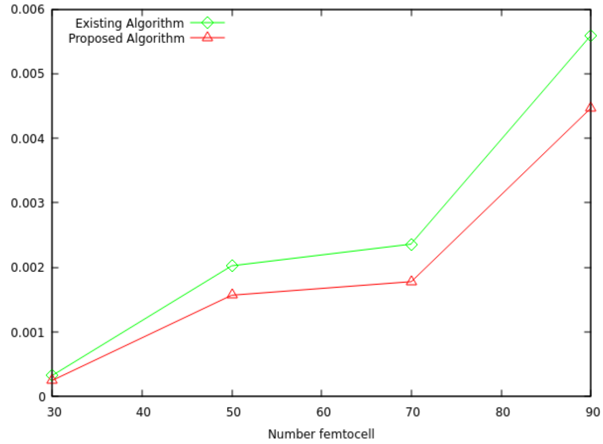

Figure 4. 15 UEs Packet Loss Ratio Comparison using VoIP Application

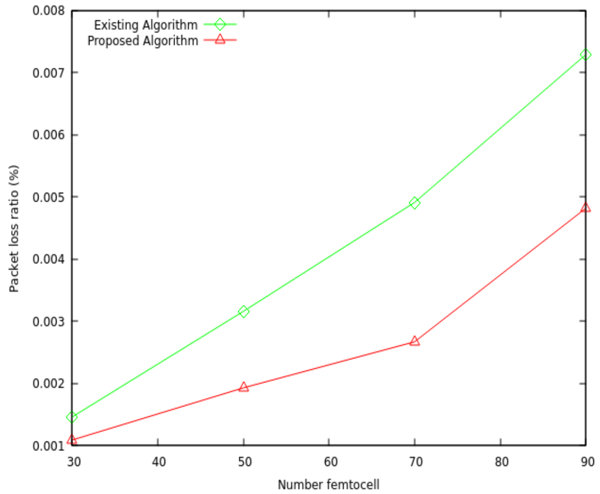

Figure 5. 30 UEs Packet Loss Ratio Comparison using CBR Application

However, the proposed algorithm reduced the Packet Loss Ratio compared to [20] handover algorithm for each UE group and for each femtocell density using the VoIP application. Generally, the proposed algorithm combined with the VoIP application reduced the Packet Loss Ratio by 89.24% compared to the [20] handover algorithm in all scenarios.

B. Discussion

The proposed algorithm increased the Packet Loss Ratio from 0.00411 to 0.0348 seconds when the femtocell number increased from 30 to 90 and in the case of using 15 UEs. Meanwhile, with [20] algorithm the Packet Loss Ratio increased from 0.00425 to 0.04952 seconds with the same change in femtocell number and the same number of UEs. In addition, in the case of 30 UEs, the proposed algorithm increased the Packet Loss Ratio from 0.00513 to 0.03942 seconds, while the Femtocell number increased from 30 to 90. With [20] algorithm the Packet Loss Ratio increased from 0.00656 to 0.05504 seconds with the same change in femtocell number using the same application.

Nevertheless, the proposed algorithm reduced the Packet Loss Ratio in comparison to [20] handover for each of both UE groups for each Femtocell density using the CBR application. In general, the proposed algorithm with CBR reduced the Packet Loss Ratio by 88.53% compared to [20] handover algorithm in all scenarios.

The proposed algorithm in the VoIP application increased the Packet Loss Ratio from 0.00025 to 0.00447 seconds when the Femtocell number increased from 30 to 90 and the number of UEs was 15. Meanwhile, with the [20] handover algorithm the Packet Loss Ratio increased from 0.0003264 to 0.0055872 seconds with the same change in femtocell number. Additionally, in the case of using 30 UEs and the same change in Femtocell number, the Packet Loss Ratio showed variation in the results in comparison to the Packet Loss Ratio when using 15 UEs with both algorithms because of the effect of the number of UEs. The Packet Loss Ratio in the proposed algorithm increased from 0.00109 to 0.00482 seconds when the Femtocell number increased from 30 to 90. In addition, the Packet Loss Ratio increased from 0.001459 to 0.00729 seconds with the same change in femtocell number for [20] algorithm. However, the proposed algorithm reduced the Packet Loss Ratio compared to [20] handover algorithm for each UE group and for each femtocell density using the VoIP application. Generally, the proposed algorithm combined with the VoIP application reduced the Packet Loss Ratio by 89.24% compared to the [20] handover algorithm in all scenarios.

Generally, the proposed algorithm shows the lowest Packet Loss Ratio for both applications when compared to the handover algorithm proposed by [20], across all UE groups and Femtocell distributions. This advantage in minimizing Packet Loss Ratio can be attributed to the efficiency of the Load Balancing integrated into the Q-learning algorithm.

Additionally, it is notable that the Packet Loss Ratio increased for both algorithms as the UE number increased from 15 to 30 for each femtocell density. This incremental trend is predictable and correlates with the rise in UE density, indicating the algorithm's sensitivity to network load.

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