LTE Handover Parameters Optimization Using Q-Learning Technique

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***Abstract*—Optimization of the LTE network is crucial to obtain the best performance. The handover margin (HOM) and time to trigger (TTT) should be chosen so that the system will have minimum number of handovers per user per second, minimum system delay, and maximum throughput. In this paper a new handover optimization algorithm for long term evolution (LTE) network based on Q-learning optimization is presented. The proposed algorithm operates by testing different values of HOM and TTT then observes the output performance corresponding to the values of these parameters, and it eventually selects the values that produce the best performance. The proposed handover optimization technique is evaluated and compared to previous work. Q-learning achieves minimum average number of handover per user and also has maximum throughput than the fuzzy logic optimization technique.**

Keywords—Q-Learning, Handover, LTE, Optimization.

I. INTRODUCTION

Long Term Evolution (LTE) is 3GPP latest radio access technology. Its main purpose is to increase capacity and speed [1]. Orthogonal frequency division multiple access (OFDMA) is the type of multiple access technique used in the downlink, while the uplink works by single-carrier frequency division multiple access (SC-FDMA) [2]. A physical resource block (PRB) is the smallest transmission unit, containing 12 sub-carriers with a total bandwidth of 180 kHz and duration of 1ms. The equivalent to a base station in the LTE network is the evolved-NodeB (eNB) [3].

In the mobile cellular system, each cell is served by an eNB. for a mobility purpose, the user equipment (UE) should move from serving eNB to another as a target so that the power received from serving cell decay while the target cell rises. To prevent the call from being dropped, the power received by the user from the serving station must not decrease below a certain value, so the user equipment may disconnect from the current serving station and connect to a new station with a better received power.

Hard handover is the main type of handover in LTE [4] and is preferred to the soft handover. The main feature of hard handover is that it has less complexity over the LTE network architecture. However, the hard handover might result in an inefficient LTE performance (i.e., increasing number of handovers and decreasing system throughput). Therefore, an optimized handover algorithm is required.

A new handover optimization technique based on Q-learning technique, to maximize the total system throughput and minimize the number of handovers is proposed in this paper using optimized handover parameters under three different speeds (10, 60, 120 km/hr) scenarios.

The paper is covering the following: Section II gives descriptions of the standard handover algorithm and the performance metrics which are adopted throughout the paper. A brief introduction to Q-learning and a detailed description of the proposed LTE handover algorithm are given in Section III. Simulation results and comparison are given in Section IV. Finally, the whole work is concluded in Section V.

II. LTE BASIC HANDOVER ALGORITHM

In this paper, the optimization technique is applied on the basic LTE handover algorithm. For the handover procedure to occur in this algorithm, the following conditions must occur: the reference signal received power (RSRP) of the target station must be greater than that of the serving station plus a certain handover margin (HOM) for a duration (HO Decision point) greater than or equal the time to trigger (TTT) as shown in Fig.1. Both HOM and TTT are used for reducing unnecessary handovers which is called "ping-pong effect".

The two conditions are expressed mathematically as follows:

$$RSRP_T > RSRP_S + HOM \tag{1}$$

$$HOTrigger \geq TTT \tag{2}$$

The system performance of the basic LTE handover algorithm is evaluated using two performance metrics which are the total system throughput and the average handovers per UE per second are defined as follows [4].

The first performance metric is the average number of handovers per second per UE.

$$HO_{avg} = \frac{HO_{Total}}{J \times T} \tag{3}$$

Where J and T are the total number of users and total simulation time, respectively and HO_{avg} and HO_{Total} are the average handovers per second per UE and the total number of successful handovers, respectively.

The system throughput which is defined as the rate of successful messages delivered over a communication channel that are sent by all users per second. The cell throughput is measured at the eNB and is mathematically expressed as [5]:

$$cell\ \ throughput = \frac{1}{T}\sum_{j=1}^{J}\sum_{t=1}^{T} tput_j(t) \tag{4}$$

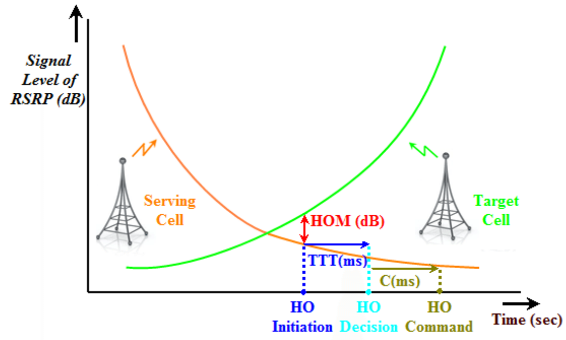

Fig. 1: Handover decision based on HOM and TTT [6]

where *T* is the total simulation time, *J* is the total number of users, and $tput_j(t)$ is the total size of correctly received bits of user *j* at time interval *t*.

The final metric is the system delay which is the average system queuing delay which is defined as the time duration from the queuing packet's arrival time at the eNB buffer to current time. It can be expressed as follows:

$$cell\ delay = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{J}\sum_{j=1}^{J}W_j(t) \qquad (5)$$

where *J* is the total number of users within the cell, *T* represents the total simulation time, and *Wj(t)* denotes the queuing delay of user *j* at time *t*.

III. PROPOSED Q-LEARNING OPTIMIZATION ALGORITHM

Q-Learning is a reinforcement learning technique which is model-free and can solve problems without requiring objective function or a model for maximizing. It achieves an optimal action selection that Markov decision process (MDP) gives. It models the environment around it to certain states and actions, and the agent uses unsupervised learning to learn about that surrounding environment. One of the states is defined to be the goal state that the agent's main objective is to achieve this goal state. The agent makes random actions which are assigned different rewards and the action that reaches the goal state has the largest reward. The learning technique then calculates a Q value for this action using the reward value assigned to it and updates this value in the action's corresponding index in the Q matrix [7]. This process is repeated until each element in the Q matrix converges. Thereafter, the agent reaches the goal state guided by this Q-matrix independent of the selected initial state [8].

In our problem, it is required to find the HOM and TTT to provide the best performance. These best performances imply maximum throughput, and minimum average numbers of handovers and system delay [9]. However, there is no direct relation between the performance metrics and the system parameters used in the optimization. Thus, a learning technique which is a model-free such as Q-Learning is needed. Thus, modeling the optimization problem as an MDP to achieve the goal state which is acquiring the best performance, and the actions are the different combinations of HOM and TTT. The main challenge of the optimization problem is that acquiring the best performance is not defined and accordingly, the goal state that should be achieved is not defined [10]. To solve this issue, all the HOM and TTT combinations defined in the range mentioned in 3GPP release are attempted [11]. Through each combination, the LTE system model is simulated including 100 UE moving randomly between 7 cells [4]. The performance metrics of total throughput, total system delay and average numbers of handover are calculated and used to get the reward value in the end of each iteration using the reward function mentioned in Algorithm 1 which clarify the proposed Q-learning optimization technique. The reward value is used to get the new Q-value which updates the element of the Q-matrix that corresponds to such HOM & TTT combination as in Algorithm 1. This simulation is repeated to ensure that the final Q-values converge in the matrix. At the end, the maximum Q-value in the matrix corresponds to the HOM and TTT values combination that achieves the best performance. The proposed algorithm is applied for the 3 velocities (10, 60, 120 Km/hr). The learning rate β used in Algorithm 1 was equal to 0.5.

Algorithm 1 shows the proposed Q-Learning optimizing technique.

Algorithm 1: Q-learning Optimization Technique

Repeat for each velocity

1- Initialize a Q-matrix of zeros

Repeat for each HOM

Repeat for each TTT

Repeat

2- After simulating the system, Calculate total system throughput, total system delay and the average handover per second for all UEs.

3- Calculate the reward function using $r = -(w_1 * HOav + w_2 * System\ Througput - w_3 * System\ Delay)$

4- Update the Q-value corresponding to the current HOM & TTT using $Q(HOM, TTT, V) = (1-\beta) * Q(HOM, TTT, V) + \beta * r$.

5- Choose the maximum Q-value out of the Q-matrix at each velocity

The weights of the reward function parameters w_1, w_2 and w_3 are 0.175, 0.65 and 0.175 respectively which are selected based on trial and error.

IV. SIMULATION RESULTS

The performance evaluation of the basic handover algorithm is optimized and compared according to the System parameters used in the simulation for downlink LTE system and given in Table 1.

Table 2 shows the simulation results of the optimized parameters for each handover algorithm for different values of the user speed [12, 13].

While Table 3 shows the simulation results of LTE basic handover algorithm for the standard LTE, methods presented in [3], [4], [14], [15] and Q-learning proposed in this paper. As listed in Table 3, the proposed Q-learning technique has better handover results when compared with all other algorithms.

The proposed Q-learning technique is better than algorithm in by a factor of 30% [4] at the expense of average number of handovers.

Table 1. Simulation Parameters

Parameters	Values
Bandwidth	5MHz (25 PBR)
Frequency	2GHz
Cellular layout	Hexagonal grid, 7 cells
Number of Users	100
Handover Event	Hard handover algorithm (A3 event)
Path Loss	Cost 231 Hata model
Shadow fading	Gaussian log-normal distribution
Multi-path	Non-frequency selective Rayleigh fading
Packet Scheduler	Round Robin
Scheduling Time (TTI)	1 ms
User's position	Uniform distributed
User's direction	Randomly choose from [0,2π], constantly at all time
Simulation time	10000 ms
TTT	{0, 1, 2, 3, 4, 5} millisecond
HOM	{0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10} dB
UE mobility speed	Low: 10 km/h Medium: 60 km/h High: 120 km/h

Table 2. Optimized Parameters

Speed [km/hr]	Proposed Technique	[6]
10	HOM = 8 TTT = 3	HOM = 8 TTT = 5
60	HOM = 8 TTT = 3	HOM = 8 TTT = 4
120	HOM = 6 TTT = 3	HOM = 8 TTT = 4

Table 3. Simulation Results

Methods	No. of handover	No. of ping-pong
Standard LTE	13.86	3.96
[3]	1.68	--
[4]	0.37	0.03
[14]	--	0.57
[15]	0.74	0.05
Proposed Work	0.22	0.015

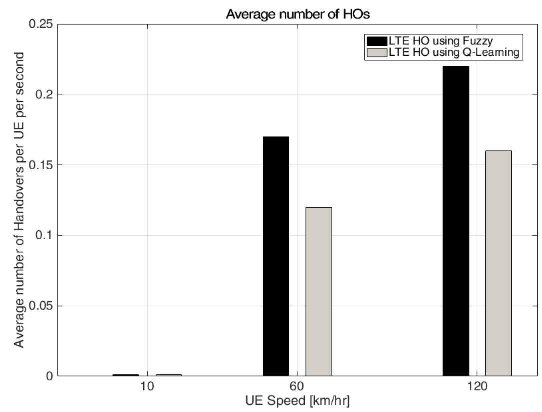

Fig. 2: Average number of HO per UE per second

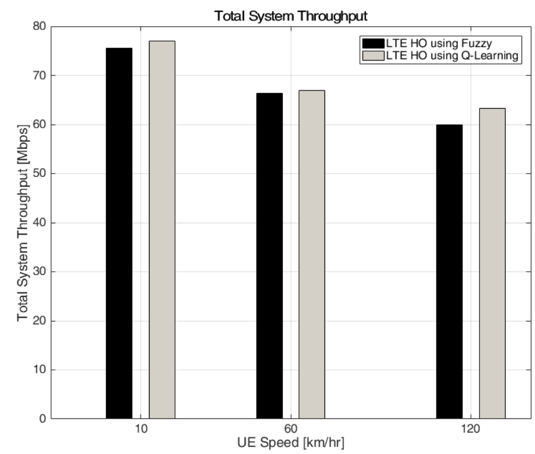

Fig. 3: Total System Throughput

Fig. 2 shows the average number of HO per UE per second calculated for the basic handover algorithm with different speed scenarios. It appears that the proposed Q-learning technique exhibits lower values as compared with the algorithm in [4], especially at 120 Km/hr.

Fig. 3 displays the total system throughput for the basic handover algorithm. The figure demonstrates that proposed technique has the highest throughput as compared with the algorithm in [4], this is because the proposed technique has the advantage that it prevents the system from making ping-pong handover that results in dropping in packets.

The system delay is portrayed in Fig. 4. The handover occurs more as the speed increases, so the system delay also increases with the increase of handovers. Besides the minimum number of HO and maximum system throughput are achieved by the proposed Q-learning optimization technique, and in addition it exhibits lower delay.

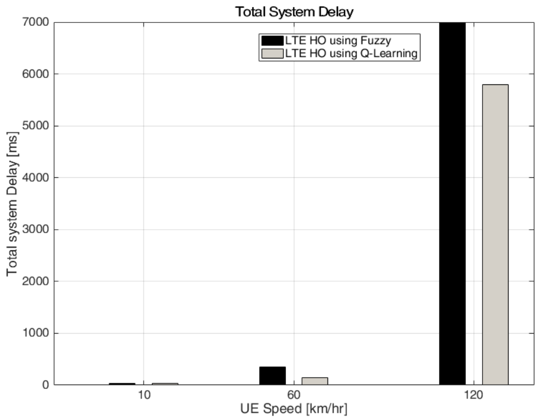

Fig. 4: Total System Delay

It is shown that the proposed optimization technique, presented in this paper, achieves lower average number of handovers compared to the algorithm in [4] by around 30%. The proposed optimization technique succeeds to increase the system throughput by 15% compared to the algorithm in [4].

V. CONCLUSION

In this work, a proposed technique based on Q-learning that learns the best HOM and TTT values is presented. The proposed technique simulation results are compared with the basic LTE handover algorithm under different UE speed scenarios. Results show that the proposed Q-learning technique effectively improves network performance (minimize the handover, maximize the system throughput, and minimize the system delay) when compared to other work in the literature.

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