5G Handover using Reinforcement Learning

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Abstract—In typical wireless cellular systems, the handover mechanism involves reassigning an ongoing session handled by one cell into another. In order to support increased capacity requirement and to enable newer use cases, the next generation wireless systems will have a very dense deployment with advanced beam-forming capability. In such systems, providing a better mobility along with enhanced throughput performance requires an improved handover strategy. In this paper, we will detail a novel method for handover optimization in a 5G cellular network using reinforcement learning (RL). In contrast to the conventional method, we propose to control the handovers between base-stations (BSs) using a centralized RL agent. This agent handles the radio measurement reports from the UEs and chooses appropriate handover actions in accordance with the RL framework to maximize a long-term utility. We also show that the handover mechanism can be posed as a contextual multi-armed bandit problem. We analyze the performance of the methods using different propagation environments and compare the results with the traditional algorithms. Results indicate that a gain of about 0.3 to 0.7 dB for few practical propagation environments.

Index terms: Handover, Mobility, Machine-Learning, Reinforcement Learning, 5G, Beamforming.

I. INTRODUCTION

One of the common ways to increase the capacity and coverage of a cellular system with a limited frequency spectrum is by partitioning the network coverage area into cells such that neighbor cells reuse the frequencies. In these systems, only way to support mobility is through a handover mechanism. This enables UEs to seamlessly move within the coverage area of the network. The handover mechanism involves reassigning an ongoing session handled by one cell into another. A UE is either in an idle or connected mode. In idle mode, the UE just camps into a cell and does not have any active signaling or data-bearers to the base-stations (cells). However, when in connected mode the base-station (cells) will allocate resources to the UEs and there will be active signaling on the data and control channels. In this paper, we describe a novel technique for connected-state intra-frequency handovers for UE in 5G context. There exist several algorithms and methods for handover in the connected state. In cellular networks, the UE continuously monitors the signal strength of the serving and neighbor cells and report them to the base stations. To illustrate the traditional handover mechanism, consider a UE moving away from the serving cell near the cell edge. As shown in Fig. 1, when the serving cell reference signal received power (RSRP) decreases below the acceptable level and the neighbor cell RSRP higher than the serving cell by a threshold (hysteresis value), then the serving base-station initiates a handover. The measurements are typically done on the downlink reference signal. This algorithm is discussed in more detail in [1], [2]. The hysteresis value ($\Delta$) along with time-to-trigger ($\beta$) is used to overcome the ping-pong effect. The algorithms in [3] and [4] discuss methods to overcome the ping-pong effect during handover. In [5], the authors discuss how to optimize the handover procedure between femto and macro cells by using information such as velocity, received signal strength (RSS), etc. In [6], two new handover algorithms specifically for railway scenarios are discussed, where the parameters such as time-to-trigger and hysteresis are optimized for high speed railway scenarios. In contrast to these works, we propose a methodology to formulate handover procedure as a reinforcement learning problem. In this strategy, the handover decisions are made by a centralised RL agent. The serving BS will forward the UE measurement reports to a centralised RL agent which will choose the handover action. We demonstrate the utility of such a formulation through simulations.

II. REINFORCEMENT LEARNING

In this Section, we will describe briefly the reinforcement learning (RL) framework and discuss how the handover optimization problem can be posed as a reinforcement learning problem. Reinforcement learning is an evaluative feedback based model-less learning paradigm as shown in Fig. 2.
the agent learns the optimal action in a given situation based on trial and error. This is achieved through exploration and exploitation. During exploitation the agent tries to take the actions that yields maximum reward, while during exploration the agent tries to take action which may not yield maximum reward instantaneously however helps the agent to discover newer actions that are profitable in the longer run.

A multi-arm bandit problem is a variant of the RL problem where the actions chosen does not alter the operating environment of the agent. The problem involves identifying the arm of a multi-arm bandit whose reward distribution is unknown through trial and error. The CMAB problem is an extension of the above which involves identifying the arm of the bandit for a given context as shown in the Fig. 3.

The handover problem can be posed as a CMAB problem (refer to Fig. 3). We propose to use a centralized CMAB agent which will control the handover actions based on the measurement data from the UE. Each arm of CMAB consists of what node the UE could be handed over to. The gain perceived by the UEs could be among others based on one or more of the following metrics: Downlink-throughput, Uplink-throughput, Power and SINR of the link-beam after handover. The context in the CMAB agent could be derived from the UE measurement. The context information could consist of power measurements for serving and target access-beams, location, speed, antenna setup, etc. The CMAB could be implemented among others using the techniques such as neural network, random forest, Q-learning, etc.

Each base-station sends the UE measurement report to the centralized CMAB agent and we derive context from the measurement report collected from the connected UEs. The CMAB action, i.e., pulling the arm of the bandit is analogous to the choosing of node to handover or to stay on the current node. The goal is to select an action that maximizes an expected reward.

The received power measurements from a subset of each neighbour and serving cell beams can be used as the context. The reward is chosen as the received power of the link-beams after the action (handover) is taken. This is further illustrated in the Fig. 4. The table shown in the Fig 4 indicates the beam power values derived from measurement report at position, $x_1$, $R_{x_1}$, which is used as the context in our CMAB formulation.

### IV. Algorithms

In this section, first we discuss the access beam based algorithm. This algorithm or its variant is commonly employed in the current wireless networks for handover. The main idea of this algorithm is that the handover is triggered by the serving base station when the access beam power of the target node is
Algorithm 1: Handover Algorithm using Access-Beams

Input: Measurement Report, \( R \)
Output: Base station to Handover, \( n \)
1 \( b_{nbrs} \leftarrow \text{getNeighborAccessBeamPower}(R) \)
2 \( b_{serv} \leftarrow \text{getServingAccessBeamPower}(R) \)
3 \( b_{max} \leftarrow \arg \max(b_{nbrs}) \)
4 \( \beta_v \leftarrow \text{getTimeToTriggerValue()} \)
5 if \( b_{max} < b_{serv} + \Delta \) then
6 \( n \leftarrow \text{getCurrentServingNode()} \)
7 else if \( b_{max} > b_{serv} + \Delta \) and \( \beta_v < \beta \) then
8 startTimerToTriggerTime()
9 \( n \leftarrow \text{getCurrentServingNode()} \)
10 else
11 \( n \leftarrow \text{getNodeId}(b_{max}) \)
12 return \( n \)

Fig. 5. Q-Table with state-action-value collection. State is derived from the measured-report. It constitutes \( N \) access-beam measurements of serving and neighbor cells together with the cell-ID of the serving cell. Actions include chosen handover cells and the value is the received link-beam power after handover.

higher than the serving base station power by a hysteresis value
for the duration greater than to-trigger parameter. This algorithm runs in each base-station and is briefly described in Algorithm 1.

As discussed in the previous section, this paper propose using reinforcement learning for devising handover strategy. Many methodologies exist for implementing the proposed formulation discussed in Section III for the handover problem using CMAB. One possible implementation of the proposed idea is through Q-Learning based design. Here, the Q-Learning agent learns by trying all actions in all states (contexts) repeatedly during training phase to learn what actions are the best. In these algorithms, the state-action-value are typically stored in a Q-Table structure. An illustrative Q-Table is as shown in Fig. 5.

The access beam-powers together with serving cell forms the “context/state” (refer to Fig. 4), target cell to handover forms “action”, and received power of the link beam after the handover forms “value/reward”. This is maintained in a table known as Q-Table as shown in Fig. 5. During the training phase this table is built and during the active phase the constructed Table is used for choosing those actions which yields larger value/rewards. For example, refer to a simple 2-node network shown in the Fig. 4. Here, when the UE moves from position \( x_1 \) to \( x_2 \), even though, at \( x_2 \) the access beam RSRP of the Node-2 is higher than that of Node-1 an handover may still be initiated to Node-1, since the value for the corresponding action of handover to Node-1 in the Q-Table is higher than for staying at Node-2. This is because the reward is derived from the received power of link-beam, and the link beam power corresponding to the Node-1 is higher than that of Node-2 (i.e. \( l_{12} > l_{21} \) at the position \( x_2 \) in Fig. 4). This is further illustrated in Fig. 6. The reward/value configuration should be derived not only based on data link beam performance but also on the ability to perform initial access and synchronization. This can be ensured by making sure that handovers are initiated only to those nodes which have sufficient access beam power for initial access and synchronization. This is referred to as \( \delta \) in Fig 6.

Since in the discussed example, the state-space is continuous, it is not possible to store all possible states/contexts in the Q-table. We construct the Q-Table which represents the state-space coarsely. This can be done by appropriately choosing the training phase. For example, the context derived from the UE measurements at coarse locations in a 2D area covering the network can be used to construct the Q-Table during the training phase. During the active phase, a similarity function

- **Environment-1**
  - Field size: 1 km X 1.5 km
  - No of base-stations: 7
  - No of access beams: [3 3 3 3 3 3]
  - No of link beams: [3 10 10 10 10 3]
  - Transmit Power (dB): [43 40 40 45 40 40 43]
  - Mobility Model: Semi-deterministic

- **Environment-2**
  - Field size: 1 km X 1.5 km
  - No of base-stations: 7
  - No of access beams: [3 3 3 3 3 3]
  - No of link beams: [3 3 3 3 3 3]
  - Transmit Power (dB): [43 40 40 45 40 40 43]
  - Mobility Model: Semi-deterministic

- **Environment-3**
  - Field size: 1 km X 1 km
  - No of base-stations: 21
  - No of access beams: [1 1 ... 1]
  - No of link beams: [8 8 ... 8]
  - Mobility Model: Semi-deterministic

Fig. 6. An illustration of power variations in link and access beams as the UE in Fig 4 moves from position \( x_1 \) to \( x_2 \). At \( t_2 \), even though the access-beam power of Node-2 is higher, the handover is still initiated to Node-1 by the RL agent since the link-gain, \( l_{12} > l_{21} \). The \( \delta \) denotes the minimum access beam power need for cell acquisition.
Fig. 8. The beam power density in a 2D area for different environments used in the performance evaluation. (A) shows the access-beam setup. (B) and (C) shows link-beam energy distributions for Environment-1 and Environment-2. (D) shows the link-beam setup for the Environment-3.

based on the minimum Euclidean distance measure between the Q-table contexts and the newly received context from the measurement report, R. This is shown in (1)

\[ c' = \min_{c \in Q} ||c - p'|| \]  

Where \( p' \) denotes the context having beam measurements and the serving cell ID during the active phase. The \( c' \) denotes the context in the Q-table (Q) with minimum Euclidean distance to \( p' \).

Equation (2), shows how the choice of the base-station is made during the active phase. Here \( V_Q(c', C_i) \) denotes the “value/reward” for choosing the cell \( C_i \) for the context \( c' \) from the Q-Table.

\[ i^* = \arg \max_i \{ V_Q(c', C_i) \} \]  

The \( i^* \) denotes the base-station index with maximum reward.

V. SIMULATION RESULTS

In this Section, we will evaluate the proposed solution with the existing method for three distinct RF environments. The Environment-1 and Environment-2 are based on the synthetic data generated from a system emulator with different configurations of the beams. Here we used a simple path-loss model having a path-loss exponent of 3.1. Environment-3 is based on the WINNER urban-macro (UMA) propagation model and is inspired by the city environment of Tokyo and Seoul. We use 7 rooftop sites with 21 base stations each having 1 access beam and 8 link beams. The configurations for the environments and the RF beam patterns for all the three environments are shown in Fig. 7 and Fig. 8 respectively.

In all the three environments, we assume a semi-deterministic mobility where UE will take steps in vertical direction and when UE hits the edge of the raster/field, it will relocate randomly to a different X-position, and the whole process will repeat again. In each step, the measurement is sent to the RL agent and a decision on the handover is made. After 10000 steps, we assess the performance using the following:

- Average received link-beam power, \( E(P_l) \)
- Probability density function (PDF) of the received link-beam power, \( p(P_l) \)

We compare the performance of the above metric with the access-beam based method having \( \Delta \) and \( \beta \) set to 0. This

3The 5G periodic measurement reporting strategy from UE to BS is employed here
Fig. 9. The performance of the proposed handover algorithm is compared with the traditional handover mechanism. The PDF of the increase in average link-beam gain, $G$, due to RL, and the PDF of the received link-beam power by the UEs under different handover strategy’s is shown in the left and right plots for different environments.

$G = \{E(P_l)_{\text{Algorithm-2}} - E(P_l)_{\text{Algorithm-1}}\}, \quad (3)$

where Algorithm-1 is traditional handover Algorithm discussed in Section I and the Algorithm-2 is the proposed RL based handover Algorithm discussed in Section IV. The PDF of gain by using RL, $p(G)$ and the PDF of the received link-beam power, $p(P_l)$ for all three environments are shown in Fig. 9. The performance in Fig. 9 is computed by repeating experiments with UE initialized to different random seeds and initial-locations. In each experiment UE mobility as described above is considered. Notice that the link gain in the Environment-2 is more than in Environment-1 this is due to higher opportunity to RL based handover to pick the better base-stations as the link-beams in this environment is narrow and penetrate deep into the neighbor cells (refer to Fig. 8). Also, for the Environment-3 which is based WINNER UMA propagation model, the results indicate a gain between [0.3 - 0.5] dB.

VI. CONCLUSION AND DISCUSSION

In this paper, we proposed a way to do handover actions in 5G systems through reinforcement learning. We showed that the handover problem can be posed as a multi-arm contextual bandit problem which can be trained offline. We developed an innovative reward configuration based on the link-beam performance, with an objective to choose the handover action which maximizes the long-term reward (link-beam performance). We showed how such a system can be developed using a Q-learning model and some of the challenges of the design such as state-space explosion can be avoided by a suitable choice of similarity function.

We assessed the performance for different deployment and propagation environments including a ITU standard based one. We demonstrated the utility of the method through the average link-beam performance using a semi-deterministic mobility model in three distinct environments. In all the considered environments, the proposed idea of this paper performs better than the existing methods. The results also indicate that when the link beams are narrow and penetrate deep into the neighbor cells, the RL based handover based handover algorithm performs better due to the increased opportunity to optimize long-term link gains.

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