

# A Novel Unified Handover Algorithm for LTE-A

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**Abstract**—In today’s mobile networks, handover (HO) decisions are performed based on static thresholds of e.g. the “Received Signal Radio Power” (RSRP) or the “Received Signal Radio Quality” (RSRQ). In LTE networks the HO Events A1-A6 have been defined. However, threshold based HO decisions often lead to poor network resource utilization, increased call blocking probabilities and provide low adaptivity w.r.t. user mobility pattern changes. In this paper, we propose a novel unified HO Algorithm based on Discrete Stochastic Dynamic Programming (DSDP), taking into account not only the radio conditions but also the overall resource utilization (i.e. the past, current and predicted future cell loads) and the impact of individual HO decisions on the serving and target cells. The HO algorithm operates in a decentralized manner – it is executed at each eNodeB (eNB) and attempts to achieve a balanced cell load. Our method can be readily integrated in legacy networks, as all required input parameters have been defined in the 3GPP rel. 11. To demonstrate the performance of the proposed algorithm, we implemented it in a NS3-GYM simulation environment and investigated an indoor LTE network scenario with X2-based HO capability.

**Keywords**—LTE mobile networks, mobility management, handover decision, autonomous resource optimization

## I. INTRODUCTION

For mobile network operators, the increase in mobile data traffic demand poses significant challenges in network planning as well as in network operation, to provide a good user experience at economically justifiable costs. One option is to apply mobility load balancing (MLB) besides normal HO procedures (triggered only by user mobility). Our goal is to develop a novel unified mobility management and resource optimization algorithm for LTE networks which can be tuned to meet different operational targets of a mobile network operator. It considers several parameters (e.g. cell loads, user mobility patterns) and performs HO decisions individually for each mobile user and comprises a set of ML-based predictor models and a DSDP problem solver. The predictor models enable the algorithm to adapt to the user mobility as well as to the cell resource occupation.

The paper is structured as follows: In Section II an overview of the state-of-the-art in HO decision algorithms is presented. In Section III a detailed explanation of our algorithm is provided. In Section IV we outline the ns3-gym simulation model which is used for the performance evaluation. Section V contains the performance evaluation results. Finally, Section VI provides a summary of our work.

## II. STATE-OF-THE-ART

Lee et al. [1] consider adaptive and normalized cost function-based HO optimization schemes for LTE networks.

However, their approach includes a user velocity estimation scheme, which cannot be deployed in practice. Jun Pan et al. [2] formulate the LTE HO decision problem as a Markov Decision Process considering the impact of burst data traffic, handover delay and handover signaling overhead. However, they lack to state an accurate estimation of the handover signaling overhead. Stephen S. Mwanje et al. [3] proposed Q-learning based algorithms for different SON tasks in mobile networks like Mobility Robustness Optimization (MRO), Mobility Load Balancing (MLB), Coverage and Capacity Optimization (CCO) and Inter-Cell Interference Coordination (ICIC). However, their approach focuses on individual SON tasks and does not provide an integrated solution (e.g. the combination of MRO and MLB). Furthermore, the convergence time and computational overhead is not considered. The approaches in [4][5][2] are of theoretical nature, i.e. the considered metrics (e.g. latency) for HO decision making are not available within standardized 3GPP signaling messages.

HO decision algorithms might benefit from predictions of user locations and movement directions [6]. Conventional localization methods normally require a minimum of 3 geographically diverse reception points for the location estimation process and usually suffer from poor accuracy. Probabilistic methods and ML-based techniques (NN, kNN and SVM) have been explored for location estimation as well [7][8]. Most of them also show poor accuracy because they rely on precise GPS or RSSI measurements which cannot be obtained in practice. In our approach we just carry out a coarse grained prediction of the next cell towards which a user will move and use this information to support the HO decision algorithm. This is practically feasible as already in 3GPP Release 8 it is stated, that an eNB could store history information about associated UEs as well as their stay duration [9]. Ying et al. [9] and Huaining et al. [10] proposed a simple probabilistic next cell estimation method based on historical data (the last visited cells and the respective times of stay) leading to a higher accuracy of the next cell estimation.

## III. UNIFIED MOBILITY MANAGEMENT AND RESOURCE OPTIMIZATION ALGORITHM

Figure 1 provides an overview of the unified mobility management and resource optimization algorithm. It comprises a cell load prediction model, a user mobility prediction model and an HO decision module based on a DSDP solver. The algorithm is executed in each eNB and periodically fetches UE measurement and cell status reports, generates predictions and makes HO decisions for each active user attached at the serving eNB. The HO execution is in line

to the procedures defined in 3GPP Release 11 [11]. In the following, the key components of the algorithm are described.

#### A. Cell load and user mobility prediction :

The user mobility prediction is based on a random forest classifier model. For details about the random forest classifier and its performance we refer to [12]. The user mobility prediction model explores user movement patterns from their cell association information history and predicts for each individual user its serving cell in the next time instances. Input for this prediction is the time series {time instance  $t$ ,  $RSRP$  of the serving cell,  $RSRQ$  of the serving cell,  $RSRPs$  and  $RSRQs$  of all other cells observed by the user}. The cell load prediction model also uses a random forest classification algorithm for estimating the serving and neighbouring cell loads several time instances ahead. Input for the load prediction is the time series of the  $C_v$  values of the serving and neighboring cells i.e. {time instance  $t$ , load  $C_v$ }. The cell loads as well as the user's possible next cells are predicted for multiple time steps into the future. We assume a prediction horizon of 4 time instances and apply a *Direct multi-step forecasting* strategy (see [13]). The forecasted values along with other UE specific environmental states are then taken as input for the DSDP-based HO decision.

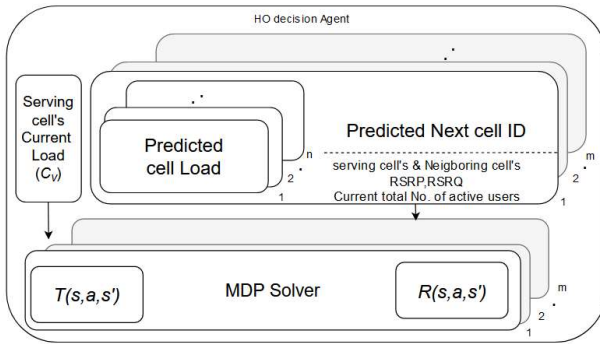


Fig. 1. Unified mobility management and resource optimization algorithm ( $n = \text{cell index}$ ,  $m = \text{UE index}$ )

#### B. Handover decision (DSDP solver):

In the following, a detailed description of the HO decision problem formulated via discrete stochastic dynamic programming (DSDP) is provided. DSDP is also referred as Markov Decision Process (MDP) in [15]. In DSDP the system state evolution is modelled as a multi-stage stochastic process (with finite horizon) exhibiting the Markov property [14] [15]. It is characterized by the 4-tuple  $(S, A, T, R)$  - State, Action, Transition probabilities and Reward [15]. The time instances at which decisions are made are named decision epochs and are denoted by  $t_1, t_2, t_3, \dots, t_N$  where  $t_N$  is last time instance of the finite time horizon. At each decision epoch an action  $a$  is performed considering the current state  $s$  - see Figure 2.

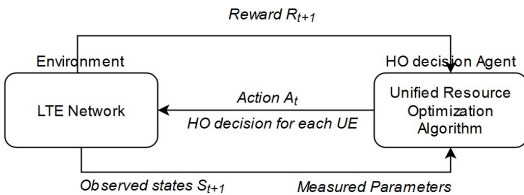


Fig. 2. Operational workflow

Related to mobility management, an action represents the decision of the next cell (current cell or a neighboring cell) an UE should be attached to considering the current state. After executing the action, the system state  $s_{t+1}$  ( $= s'$ ) and the corresponding value function  $v^{k+1}$  are updated. The goal is to optimize the expected total reward  $r(s, a, s')$  for each individual user. In the following, the main elements of the DSDP model in the context of mobility management and resource optimization are explained.

1. *States S*: The state space is denoted by  $S$ . For mobility management and resource optimization, the states are given by the occupied resources  $C_v$  (i.e. the load) of the cells. As our algorithm is executed at each eNB, the considered state space comprises the load of the serving and of all neighboring cells. The load is expressed as a linear metric: '0' indicates an empty cell (all cell resources available) and '100' indicates that no cell resources are available (full occupation) [11]. The  $C_v$  values are periodically exchanged between neighboring eNBs via the X2 interface [11]. In order to reduce the computational effort of our algorithm we consider a reduced state space by dividing the  $C_v$  value range into 4 segments (i.e. sub-states:  $S_x$ ): low load  $C_v \leq 25$ , medium load  $25 \leq C_v \leq 50$ , high load  $50 \leq C_v \leq 75$ , very high load  $75 \leq C_v$ . For instance, a cell load  $C_v = 33$ , then mapped to sub state  $S_3$ .

2. *Actions A*: The action space represents the possible decisions to which cell an UE should be attached next. The concrete decision for each UE is determined as solution of the DSDP problem (by the DSDP agent) at each epoch. Thus the action space for each user is represented by  $A = \{1, 2, 3, \dots, n\}$  assuming that an UE can be attached to  $n$  possible cells (including the current serving cell and all neighboring cells that are sensed with sufficient radio signal strength).

3. *Transition Probabilities  $Tr = T(s, a, s')$* : The state transition probabilities can be represented through a 3-dimensional matrix of size  $(S, S, A)$ . The state transition probabilities are estimated from the collected historical cell loads as well as from the predicted cell loads at each epoch. The matrix elements define the probability  $Tr$  of a transition from a sub-state  $S_x$  at time instance  $t$  to a sub-state  $S_y$  at time instance  $t+1$  in case an action  $a$  is executed [2]:

$$Tr = T(s, a, s') = \text{Prob}(S_y | S_x, a)$$

4. *Rewards  $R = R(s, a, s')$* : The rewards  $R$  can be represented as 3-dimensional matrix of size  $(S, S, A)$ . Each action  $a$  leading to a state transition from sub-state  $S_x$  at time instance  $t$  to sub-state  $S_y$  at time instance  $t+1$  generates a reward  $R$ . We define the reward as a term with 6 variables  $S_x: S_y = a, U_L, R_P, R_Q, L_M, N_{CellID}$ :

$$R = \alpha + \frac{1}{(U_L)^A} + \frac{1}{(R_P)^B} + \frac{1}{(R_Q)^C} + \frac{1}{(L_M)^D} + \ln(N_{CellID}^{t+n} + 1)$$

where  $A, B, C, D$  are parameters to control the impact of the components on the reward. We apply the parameter setting  $A = B = C = D = \log_e(W)$  where  $W$  represents the prediction horizon (expressed as number of time steps). In our study  $W=4$  is assumed, yielding  $A, B, C, D = 0,35$ .

a) *Reward Component 1 ( $\alpha = S_x: S_y$ )*: It accounts for the state transition from a sub-state  $S_x$  to a sub-state  $S_y$ . A transition from a lower sub-state (low load) to a higher sub-

state (high load) (i.e.  $x < y$ ) yields a low reward value and vice versa [16]. By this, any action  $a$  leading to a lower cell resource utilization is preferred.

*b) Reward Component 2 ( $1/(U_L)^A$ ):* It accounts for the amount of cell resources (PRBs) a user occupies. Thus it accounts for the impact of a user on the load of a cell after a HO to this cell. The motivation is to improve the HO success rate by estimating the post HO load situations in the considered set of HO candidate cells.

*c) Reward Component 3 ( $1/(R_P)^B$ ):* It accounts for the cell specific signal strength RSRP. A cell which offers a better signal strength is preferred for HO. Accordingly, the higher the signal strength is, the higher is the reward and vice versa.

*d) Reward Component 4 ( $1/(R_Q)^C$ ):* It accounts for the cell specific RSRQ. A cell which improves the channel conditions of the user is preferred. Accordingly, the higher the received signal quality is, the higher is the reward and vice versa.

*e) Reward Component 5 ( $1/(L_M)^D$ ):* It accounts for the predicted mean load of a cell averaged over the next  $n$  time instances (we set  $n=4$ ). The higher the estimated mean cell load is, the lower is the reward and the lower is the chance that the respective cell is selected as target cell for HO.

*f) Reward Component 6 ( $\ln(N_{(t+n)}^{CellID} + 1)$ ):* It accounts for the predicted cell in which a user will move within the next  $n$  time intervals. (we set  $n=4$ ). Accordingly, the higher the probability that a user moves to a specific cell is (in the prediction horizon), the higher is the chance of choosing this cell as target cell for HO.

*5. Optimality equations:* Let  $v^\pi(s)$  denote the value of being in a specific state  $S$ , given the policy  $\pi$ . A value iteration based DSDP solver uses the value iteration algorithm to solve a discounted ( $\gamma$ ) DSDP by solving the Bellman equations [10]. The optimality equations are as follows [2]:

$$v(s) = \max_{\pi \in \Pi} V^\pi(s) \quad (1)$$

$$v(s) = \max_{a \in A} \{R(s, a) + \alpha \sum_{s'} T[s', s, a] v'(s')\} \quad (2)$$

From equation (3) it is evident that a solution could be obtained both for an infinite time horizon (where the termination state is at infinity) or for a finite time horizon. The termination state is considered as the state after the HO. Accordingly, in our case equation (2) is modified as follows:

$$v(s) = \max_{a \in A} \{R(s, a) + \alpha \sum_{s'} T[s', s, a] v'(s')\} \quad (3)$$

#### IV. NS3-GYM SIMULATION MODEL

For the performance evaluation of our approach we consider the NS3-Gym simulation framework (ns-3 with Open AI Gym). For detailed information on the NS3-Gym platform, we refer to the work of Piotr Gawłowicz et al. [17]. The parameters used in the simulation and their values are depicted in Table 1.

##### 1. Network scenario

For the performance evaluation we consider an specific indoor scenario, the so-called ICT cubes layout [18]. In Figure 3 the placement of the eNB's are shown assuming an indoor area of 10,000sqm size with equally sized rooms of 100sqm.

##### 2. User traffic demand

In the simulation, 21 UEs are used. Both high load as well as low load situations are simulated (see Chapter V). Each UE has one default bearer (with UDP traffic) and two dedicated bearers (one with TCP traffic and the other with UDP traffic).

##### 3. User mobility

A realistic modeling of the mobility patterns of the users is quite challenging [19]. In this work, the user movement is mimicked using various memory-less movement models (UE1-UE6 & UE9-UE12: 2D random walk, UE13-UE15 Gauss-Markov, UE7-UE9 & UE16-UE21: random direction model).

##### 4. Gym Agent

The UE and cell specific measurements ( $RSRP$ ,  $RSRQ$ ,  $C_r$ ,  $MCS$ , etc.) are periodically (at each sample time instance) transferred from the NS-3 environment to the Gym python agent. By utilizing the ML-library scikit-learn and the MDP-toolbox, the HO decision algorithm is implemented as described in Section II. Table 2 shows the configuration parameters applied at the DSDP solver and at the Random Forrest Classifier within the Gym agent.

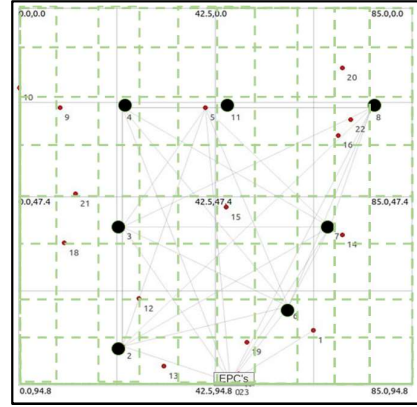


Fig.3. Locations of eNBs and UEs within the indoor area (black nodes are eNBs and red dots are UEs)

Table 1 Simulation Parameter Settings

Description	Value
Number of simulated time instances	60
Total number of eNBs	7
Tx power of each eNB	0dBm
Total number of UEs	21
UE speed	1-1.5 m/s
LTE MAC scheduler	Proportional fair scheduler
Simulation area	10,000sqm
NS-3 environment event step time	1 sec
Open AI gym event step time	1 sec
Indoor radio propagation model	ITUR P.1238-7 [20]
User traffic model	1 Default bearer (UDP) 2 Dedicated bearer (UDP+TCP)
UE mobility models	Gauss-Markov, 2D random walk, Random direction model.

Table 2: Configuration parameters

Description	Value
DSDP Solver	$\epsilon : 0.01 ; \gamma : 0.1 ;$ max iterations : 100
Random Forrest ML Classifier	N-estimator : 100; max-depth : 7 ; max features : 1

## V. PERFORMANCE EVALUATION

Usually metrics like HO success/failure rate, number of HO ping-pongs, per user throughput, HO latency and RSSI change rate are used to evaluate the performance of HO algorithms. In this work we also consider the MCS index applied to user connections (representing the spectral efficiency), the cell loads (representing the radio network resource utilization) and the HO rate per UE as performance evaluation metrics.

Figure 4 depicts the resource utilization of eNB3 and eNB1 over time. It can be seen that the cell load fluctuations are less in case of our algorithm compared to the conventional threshold based HO method. Thus the resource balancing works better, leading to an increased call admissions success rate and better utilization of under loaded cells.

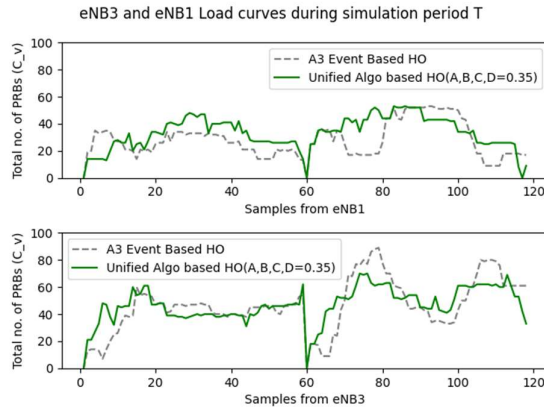


Fig 4. Resource consumption of eNB3 and eNB1

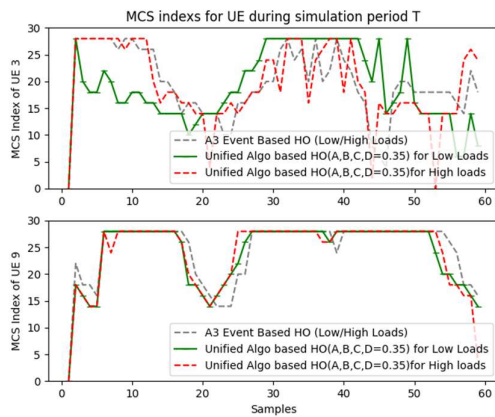


Fig 5. MCS index for UE3 and UE9

A high MCS index indicates 1) A good signal quality  $SINR$  at the UE, and 2) A high throughput as more data can be transmitted per time unit using the same number of Physical Resource Blocks (PRBs). Figure 5, depicts the achieved MCS index for a specific UE over time. It can be seen that in high

load situations, the algorithm attempts to optimize the network resource utilization by handing off the UE to less loaded cells without affecting the user throughput (remark: the fluctuations are due to HO events). Thus, the average throughput for UEs remains similar compared to the conventional threshold based HO method despite the superior load balancing capability of our algorithm.

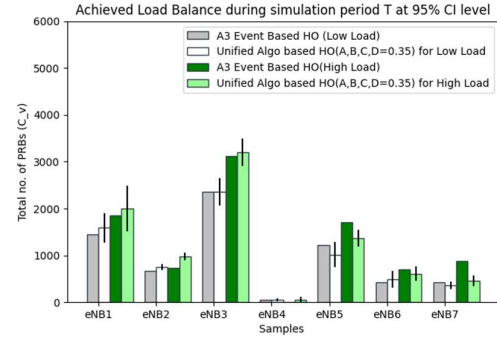


Fig 6. Average loads of all eNBs

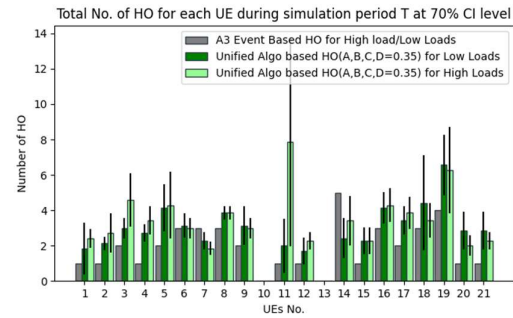


Fig 7. Total number of HOs per UE

The overall load balancing performance can be observed in Figure 6. Note, that Figure 6 has to be viewed in conjunction with Figure 4 and 5. Figure 7 shows the total number of observed HOs for each UE for both the low and the high traffic load case. It can be seen, that there exists a tradeoff between the number of HOs and the achieved load balancing.

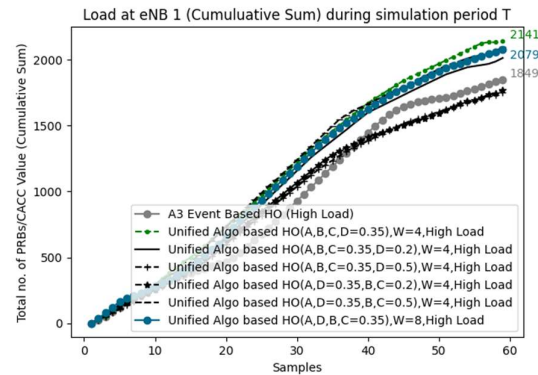


Fig 8. Load of eNB1 (occupied PRBs) over time w.r.t. different settings of the A, B, C, D parameters

Figure 8 shows the load of eNB1 (in terms of occupied PRBs) over time w.r.t. different settings of the A, B, C, D parameters. These parameters can be used to influence the impact of the respective reward component according to the

preferences of the network operator. It is inextricable that improving one performance metric will lead to a degradation of the other metrics. For example, if an operator wants to improve the channel quality of UEs, he has to tune the parameters B and C accordingly (e.g. set  $A=D=0.35$  and  $B=C=0.2$ ). But, this greedy setting would lead to unbalanced cell loads and utilization of cell resources (as can be seen from Figure 8 and Figure 9). This in turn causes a reduction of the available PRBs (although the SINR is fairly good) in some cells and a degradation of the average UE throughput. Table 3 shows the total number of handover ping-pong events during the simulation period. It can be inferred that our algorithm with default parameter settings and convenient prediction window size ( $W=4$  and  $W=8$ ) achieves a competitive performance compared to a conventional HO algorithm.

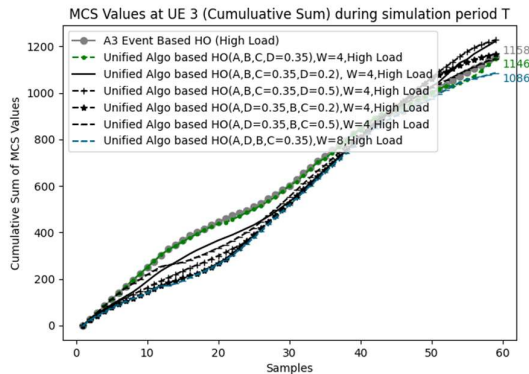


Fig 9. Cumulative sum of MCS index values for UE3 over time w.r.t. different settings of the A, B, C, D parameters

Table 3. Total number of HO Ping-Pong events

Scenario	Ping-Pongs
A3 Event Based HO (Low/High Loads)	0
Unified Algo based HO(A,B,C,D=0.35), W=4, Low Load	4
Unified Algo based HO(A,B,C,D=0.35), W=4, High Load	1
Unified Algo based HO(A,B,C=0.35,D=0.2), W=4, High Load	5
Unified Algo based HO(A,B,C=0.35,D=0.5), W=4, High Load	3
Unified Algo based HO(A,D=0.35,B,C=0.2), W=4, High Load	4
Unified Algo based HO(A,D=0.35,B,C=0.5), W=4, High Load	7
Unified Algo based HO(A,B,C,D=0.35), W=8, High Load	0

## VI. CONCLUSION

This work focuses on mobility management and resource optimization in LTE networks and proposes a novel DSDP based HO algorithm. The performance evaluation shows its superior load balancing capability compared to conventional (event A3 based) HO algorithms. It also yields good channel conditions for each UE irrespective of their mobility behavior and a fair tradeoff in the total number of HOs per UE. In our future work, we intend to extend our algorithm so that it could be also applied in 5G networks.

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