A ML based empirical Model for next Cell-ID Prediction

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Presentation Overview

- Motivation
- State-of-the-Art - User Movement Prediction Methods
- Novel next Cell-ID Prediction Method
- ns3-Gym Simulation Model
- Performance Evaluation
  - Considered HO Schemes
  - Results
- Summary

Motivation

- Motivation:
  - Development of a next Cell-ID prediction method applying ML (Classification Algorithm)
  - Easy integration of the next Cell-ID prediction method into legacy mobile networks to support mobility management
  - Performance evaluation and comparison with traditional analytical prediction approaches
- Key features of the novel next Cell ID prediction method:
  - User specific
  - High prediction accuracy
  - Radio condition awareness
  - Adaptiveness (continuous learning)

State-of-the-Art - User Movement Prediction Methods

Reference	Proposed Model	Input	Output
[7] 2011	Extended self-learning KF (Kalman Filter) and HMM (Hidden Markov Model)	Position, speed, direction	Next cell to be visited
[8] 203	MLP-Multi Layer Perceptron and PNN-Polynomial Perceptron Network	Time, X and Y coordinates	X and Y coordinates
[9] 2014	The J48 Tree model for generating C4.5 decision tree	Place, day, Manhattan and hamming distance, person correlation	UE Position
[10] 2017	Use Voronoi diagram for positioning then use the Markov model	Region in a cell Time key Traffic Hub (KTH)	Probability of next region
[11] 2017	SVM-based location prediction method	latitude, longitude, Distance and time	UE Position
[12] 2017	Naïve Bayes	Received signal strength (RSS), X and Y coordinates	Probability of next location
[13] 2019	Convolutional Neural Networks with transfer learning	Mobility Matrices	Next location to be visited
[5] 2009	Mobility history database and mobility pattern matching	Number of users in the cell, Average UE dwell time and total number of HO	Probability of next HO
[2] 2014	Moving direction prediction assisted HO scheme	Position, distance, direction	Target eNodeB
[14] 2016	ESPIRIT and Kalman filter for time of arrival Tracking	Velocity, acceleration, direction and time.	X and Y coordinates

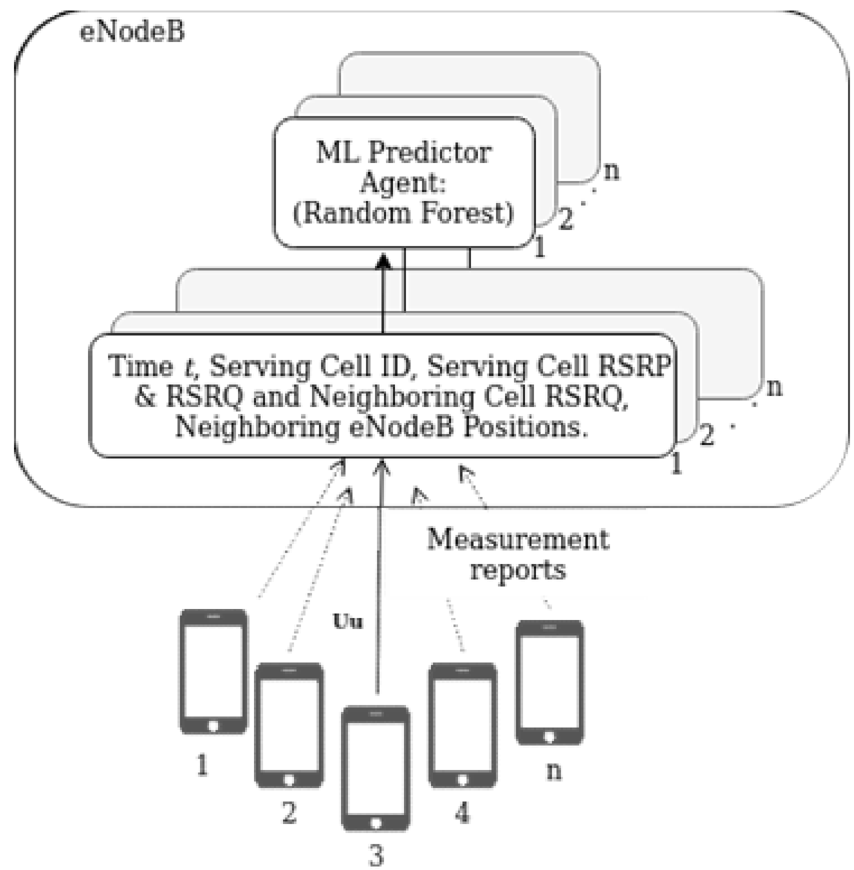
Novel next Cell-ID Prediction Method

Problem statement:

- predict the user movement w.r.t. its cell association some time steps ahead

Solution approach:

- Supervised ML algorithm (Random Forest) & direct multi step forecast strategy
- Inputs:
  - Present Time
  - Serving cell-id
  - Serving cell RSRP and RSRQ
  - Neighboring cells RSRP and RSRQ
  - Positions of neighboring eNodeBs (optional)
- Outputs:
  - Predicted cell-IDs several time steps ahead (prediction horizon: 1, 5 , 10 time steps)

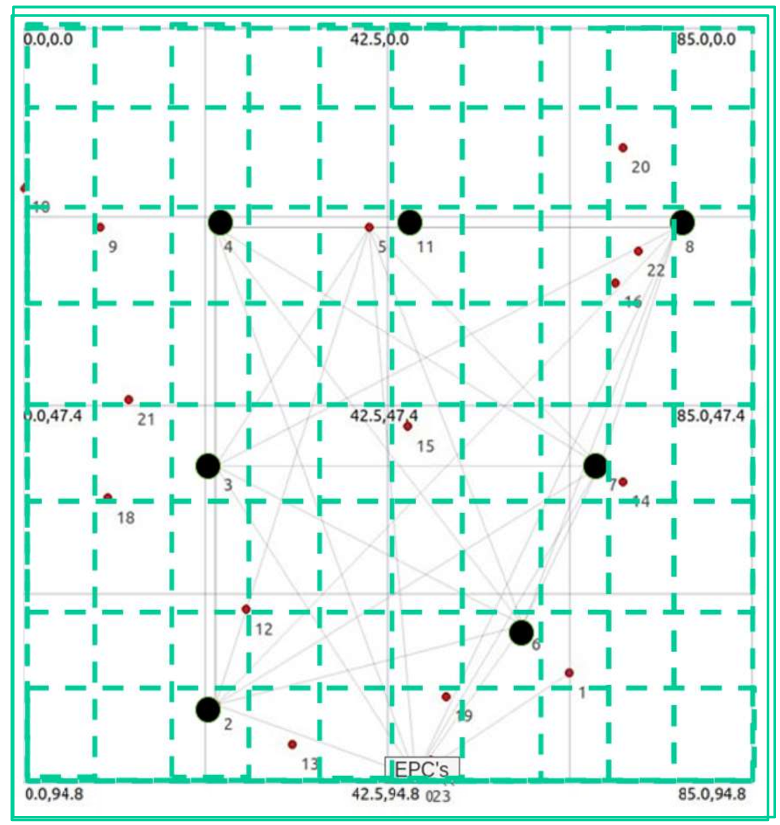


ns3-Gym Simulation Model

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	150x150 sqm
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.

Description	Value
Random Forrest ML Classier	N-estimator : 100; max-depth : 7; max features : 1



150 meters

150 meters

Network Scenario (indoor)

eNodeB

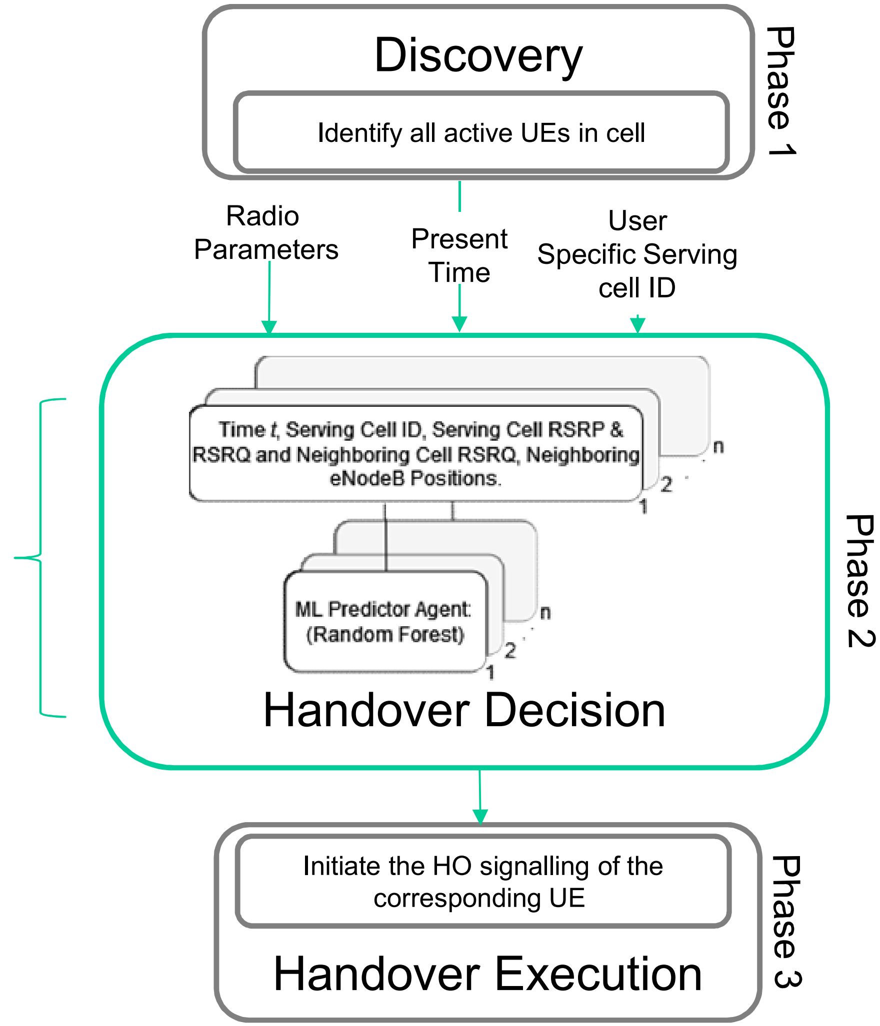
UE

Performance Evaluation – Considered HO Schemes

(1) HO scheme with ML-based next cell-ID prediction

Algorithm 1 : ML based HO Algorithm with prediction window size W

```
Start.
  for each UE do
  predict the eNodeBs to which the UEs might be associated within W
  choose the eNodeB which occurs most frequently as target eNodeB
    if the UE can sense the target eNodeB
      then perform a HO to the target eNodeB
      else keep the current eNodeB (no HO)
    endif
End
```



Performance Evaluation – Considered HO Schemes

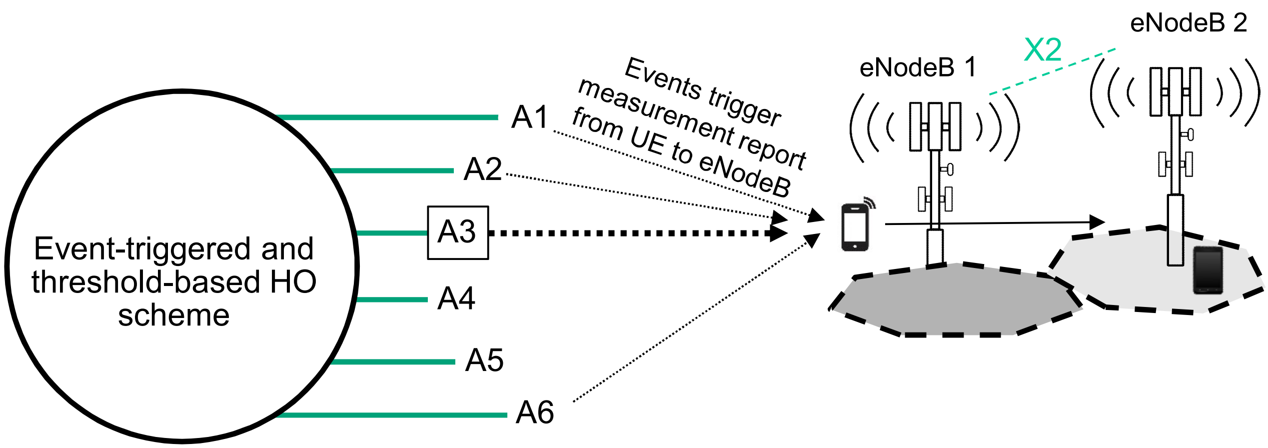
(2) Event triggered and threshold based HO scheme

- Example: A3-event triggered HO decision

$$M_t + Of_t + Oc_t - Hys > M_s + Of_s + Oc_s + Off$$

M_t,M_s = RSRP measurement results (target and serving cell)
Of_t,Of_s = Frequency specific offset (target and serving cell)
Oc_t,Oc_s = Cell specific offset (target and serving cell)

- Drawback: does not consider user movement and load of neighboring cells



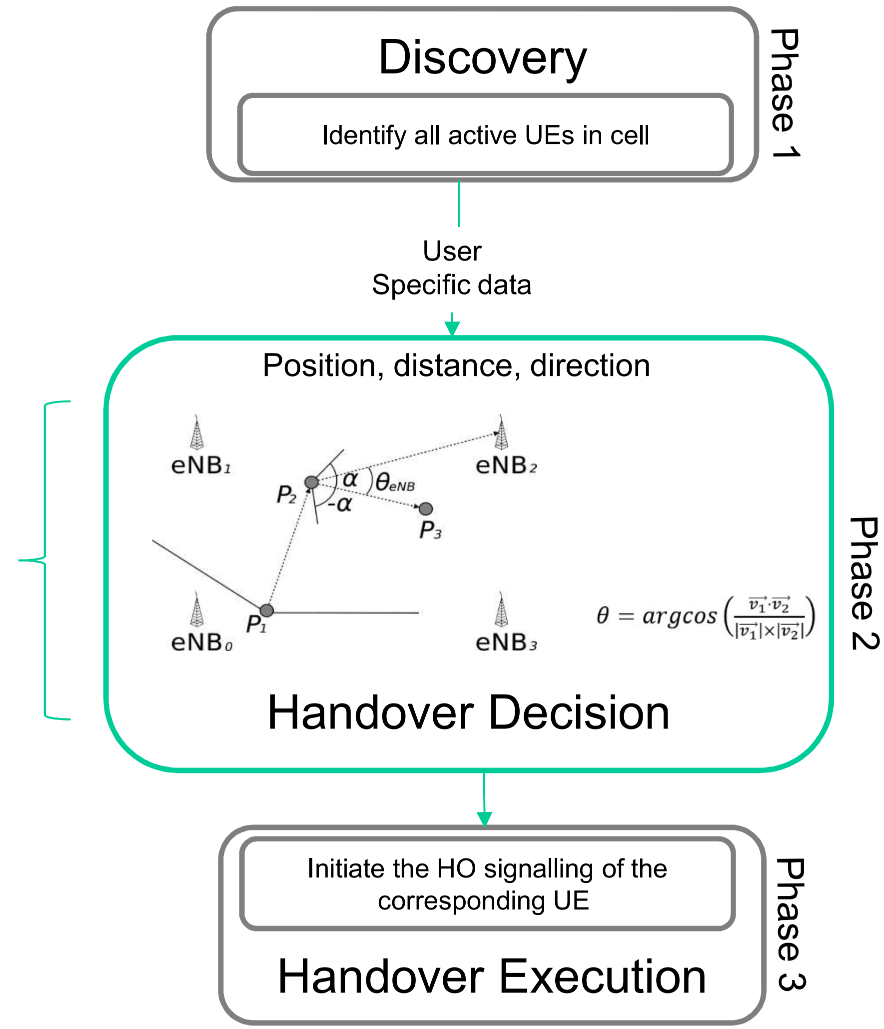
Performance Evaluation – Considered HO Schemes

(3) UE movement direction prediction assisted HO scheme

Algorithm 2 : Direction prediction-assisted handover procedure

```
for each UE do
    θ = f(P1, P2, P3)
    if θ ≤ | α | then
      for each eNodeB which can be sensed by the UE do
            θ_eNodeB = f(P2, P3, P_eNodeB)
            if θ_eNodeB ≤ | α | then
                  Q ← eNodeB
            end if
    end for
      for each eNodeB ∈ Q do
      assign weight to each eNodeB: W_eNodeB
      end for
  else
      Reset W_eNodeB of all eNodeBs to 0
      P1 ← P2
      P2 ← P3
  end if
  Target eNodeB= eNodeB with maximum W_eNodeB
  if RSRP target cell > (RSRP serving cell + Hysteresis) at least for the duration TTT then
        Handover to the target eNodeB.
        Reset W_eNodeB of all eNodeBs by 0
  end if
  end while
end for
```

Where:
- P_1, P_2, P_3 : current, previous and per-previous user position
- V_1, V_2 : vectors pointing from P_1 to P_2 and from P_2 to P_3 respectively
- $\pm\alpha$: threshold angle
- θ_eNodeB : angle towards eNodeB
- d : distance between UE and eNodeB
- P : set of UE positions (P1, P2, P3) at current time
- Q : set of eNodeBs (initially empty)
- TTT : time to trigger

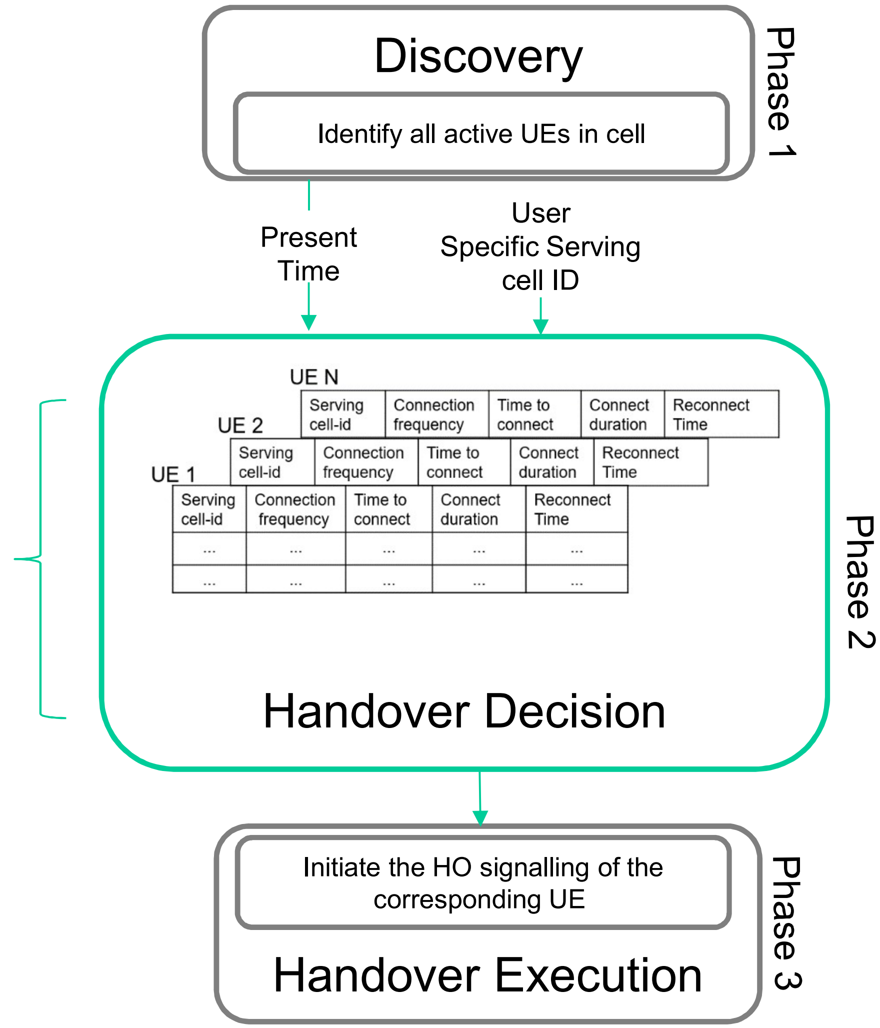


Performance Evaluation – Considered HO Schemes

(4) UE history aware HO scheme

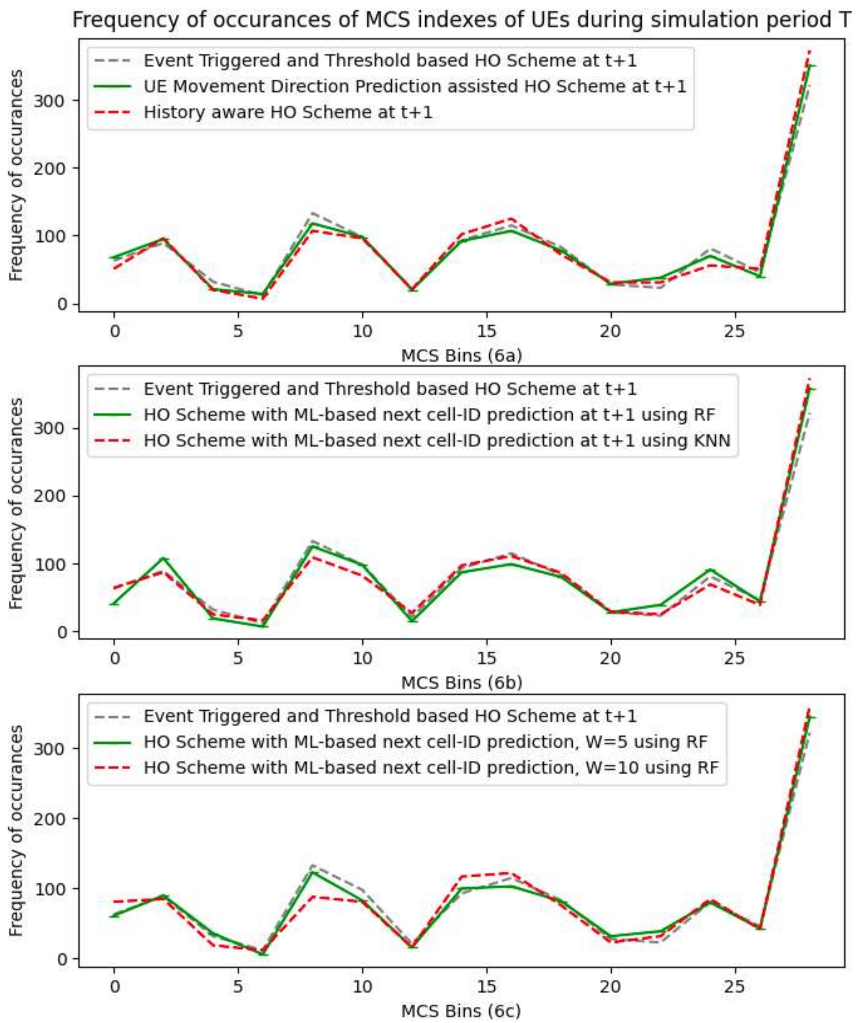
Algorithm 3 : History aware HO procedure

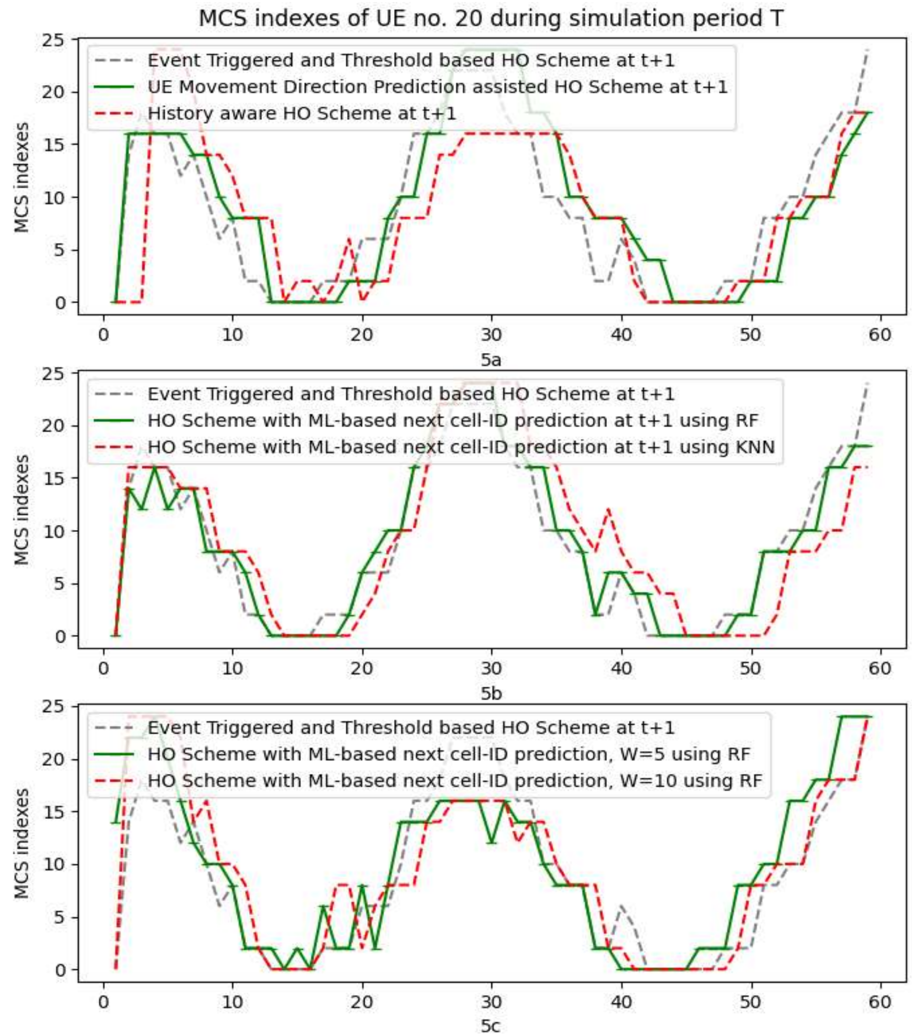
```
Start.
Tabulate the visited Cell ID history and sojourn time for each UE.
Extend each table with connection frequency, connection time instance and number of re-connections
 for each associated UE do
   if re-connections occur then
      Discard the chosen eNodeB
   else if the connection frequency is non-zero then
        if the connection time instance matches the present time t then
            if connection duration is non-zero then
               if target cell RSRP/RSRQ > then serving cell RSRP/RSRQ then
                   execute HO
               end if
            end if
         end if
   end if
end for
End.
```



Performance Evaluation – Results

(1) Impact on Radio Channel Conditions (MCS)





Performance Evaluation – Results

(2) Impact on average number of HOs and Ping Pong events

Cases	HO	Ping Pong
Event triggered and threshold based HO scheme	2.90	0.14
UE movement direction prediction assisted HO scheme	3.95	0.95
History aware HO scheme	3.90	0.90
HO Scheme with ML-based next cell-ID prediction, W=1, RF model	3.62	0.81
HO Scheme with ML-based next cell-ID prediction, W=1, KNN mod.	3.52	0.90
HO Scheme with ML-based next cell-ID prediction, W=5, RF model	1.71	0.76
HO Scheme with ML-based next cell-ID prediction, W=10, RF model	2.09	1.04

⇨ the number of HOs and Ping Pong events depend on the prediction window size *W*

(3) Prediction performance for different ML models & prediction windows

	ML Classifier	t+1	t+2	t+4	t+6	t+8	t+10
Accuracy	RF	0.97	0.95	0.93	0.91	0.88	0.87
Recall rate		0.97	0.95	0.93	0.91	0.88	0.87
F1 score		0.97	0.95	0.93	0.91	0.88	0.87
Accuracy	KNN	0.96	0.94	0.92	0.90	0.88	0.85
Recall rate		0.96	0.94	0.92	0.90	0.88	0.85
F1 score		0.96	0.94	0.92	0.90	0.88	0.85

Summary

- Presentation of a novel ML-based approach for estimating the next cell associations of a user over a prediction horizon *W*
- The integration of our approach into a simple HO scheme can lead to a better HO performance (w.r.t. the number of HOs and Ping Pong events) than conventional HO schemes
- Outlook: application of our approach to support Mobility Load Balancing (MLB) and Mobility Robustness Optimization (MRO)

Questions?

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