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RESEARCH ARTICLE

Group vertical handoff management in heterogeneous networks

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ABSTRACT

Traditional vertical handover schemes postulate that vertical handovers (VHOs) of users come on an individual basis. This enables users to know previously the decision already made by other users, and then the choice will be accordingly made. However, in case of group mobility, almost all VHO decisions of all users, in a given group (e.g., passengers on board a bus or a train equipped with smart phones or laptops), will be made at the same time. This concept is called group vertical handover (GVHO). When all VHO decisions of a large number of users are made at the same time, the system performance may degrade and network congestion may occur. In this paper, we propose two fully decentralized algorithms for network access selection, and that is based on the concept of congestion game to resolve the problem of network congestion in group mobility scenarios. Two learning algorithms, dubbed Sastry Algorithm and Q-Learning Algorithm, are envisioned. Each one of these algorithms helps mobile users in a group to reach the nash equilibrium in a stochastic environment. The nash equilibrium represents a fair and efficient solution according to which each mobile user is connected to a single network and has no intention to change his decision to improve his throughput. This shall help resolve the problem of network congestion caused by GVHO. Simulation results validate the proposed algorithms and show their efficiency in achieving convergence, even at a slower pace. To achieve fast convergence, we also propose a heuristic method inspired from simulated annealing and incorporated in a hybrid learning algorithm to speed up convergence time and maintain efficient solutions. The simulation results also show the adaptability of our hybrid algorithm with decreasing step size-simulated annealing (DSS-SA) for high mobility group scenario. Copyright © 2015 John Wiley & Sons, Ltd.

KEYWORDS
vertical handoff; group vertical handoff; heterogeneous networks; congestion game; nash equilibrium; decreasing step size-simulated annealing

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1. INTRODUCTION

A heterogeneous network is consists of different Radio Access Technologies (RAT) such as High-Speed Downlink Packet Access (HSDPA), Long Term Evolution (LTE), Wireless Local Area Network (WLAN), and Worldwide Interoperability for Microwave Access (WiMAX) networks. In case of group mobility (e.g., a group of passengers equipped with mobile terminals on board a bus or train) whereby a group of mobile terminals enter into the service area of a heterogeneous network, the selection (by each mobile terminal) of a suitable RAT is a crucial decision. Such RAT selection is not supposed to be done in a random way, but rather on the basis of certain criteria such as radio signal strength (RSS), quality of service (QoS) parameters [1,2], quality of experience (QoE) criteria [3,4], individual consideration and contextual information [5], handoff cost in the uncertainty of QoS parameters [6], and signal to interference plus noise ratio (SINR) parameter [7]. However, most state of the art RAT selection mechanisms and schemes do not consider the impact introduced by decisions of other mobile terminals. As generally known, in wireless networks, the resources are shared by all mobile terminals sharing the same locality and connecting to the same heterogeneous network [8]. It is therefore of vital importance to take into account decisions of other mobile terminals in the RAT selection prior to performing any vertical handover. However, this is only possible when mobile terminals connect to the network in

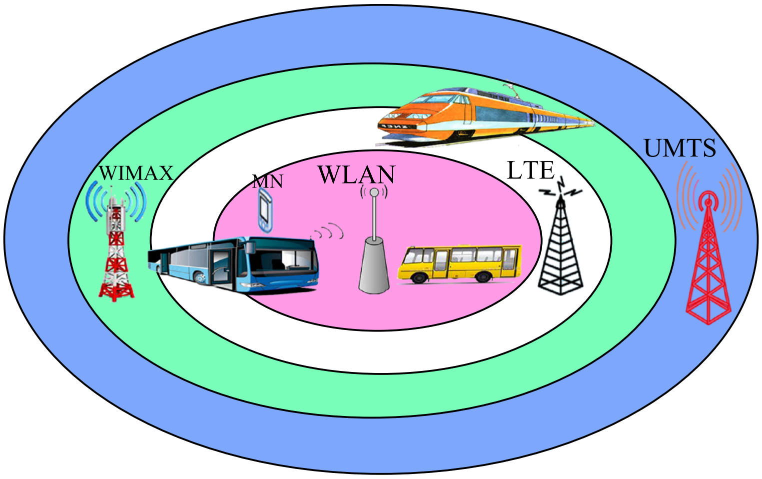

Figure 1. Some group vertical handoff scenarios in heterogeneous networks.

a sequential manner (i.e., one after another). Indeed, when mobile terminals connect to the network at nearly the same time (i.e., in case of a group mobility followed by a Group Vertical Handoff - GVHO - Figure 1), the performance of the network may degrade as it is more likely to have all mobile terminals selecting the same RAT at the same time, resulting in the congestion of the selected RAT and potentially under utilization of the other RATs. Even when the QoS perceived by mobile users drop and mobile terminals decide to switch from the initially selected RAT to another one deemed more suitable (e.g., for its higher bandwidth offering), they may do so at the same time selecting the same RAT, a fact that may result again in the overload of the selected RAT. These bad selections of RAT may occur every time there is a need to perform handoff and may continue for longer times, a fact that may become noticeable by users and may consequently heavily impact QoE. It becomes therefore of vital importance to devise agile RAT selection mechanisms that reduce the likelihood of mobile terminals selecting the same RAT in case of group mobility. This defines the core objective of this paper. We will demonstrate how this can be achieved based on game theory and particularly illustrate how the congestion game theory can help in alleviating the aforementioned issue.

The remainder of this paper is organized as follows. Section 2 discusses some related work. We present the game theory model of the envisioned congestion game in Section 3 and the stochastic approximation algorithms in Section 4. Preliminary simulation results and their analysis are presented in Section 5. The fast convergence adapted to highly mobile groups is demonstrated in Section 6. Finally, the paper concludes in Section 7.

2. RELATED WORK

A large library of research work has been conducted to support the connection of highly mobile nodes to mobile networks in a reliable and stable manner [9,10]. Some solutions are specifically tailored to support group mobility in wireless networks [11]. In [12,13], network access of a group of mobile users (on board vehicles, and travelling in the same direction and at the same speed) is coordinated by clustering the mobile nodes into a number of clusters and selecting a head for each cluster. The cluster head is in charge of relaying communication packets of mobile nodes in its cluster to the mobile network. In this manner, instead of having all nodes communicating to the mobile network, only one node communicates to the network. This shall help in alleviating congestion and facilitate the handoff operation of all cluster nodes. Group handoff of a group of mobile users to a target cell can be also anticipated and handled by a partner, already connected to the target cell and selected based on different criteria, similar in concept to [14] and in return of some incentives. In [15], a novel authentication framework with conditional privacy-preservation and non-repudiation has been proposed, to ensure security service in both inter-vehicle and vehicle roadside communications. In [16], a novel opportunistic service differentiation scheme has been suggested as an enhancement to wireless access in vehicular environment. Energy efficiency in vehicular environment has been proposed in [17,18].

In the context of heterogeneous mobile networks, a wide plethora of vertical handover algorithms have been proposed [3,4,19]. In [20], a vertical handover approach is proposed for mobile terminals assumed to connect to the network one after another. This scheme is intuitively not suitable to handle GVHO scenarios, not to mention that in its RAT selection, mobile terminals performing handover do not consider decisions taken by other terminals sharing with them the wireless medium. In [21], three network selection algorithms are proposed for GVHO scenarios using the concept of social cost, introduced in game theory and computed as a function of transfer latency. The first algorithm assumes that each mobile node knows the traffic load of all other nodes, and the selection result is achieved with a nash equilibrium in polynomial time.

The two other algorithms delay the RAT selection decision of each mobile node by a random value and that is in order to avoid the congestion that may be otherwise caused by simultaneous individual selections of networks by all mobile terminals. Research work presented in [22] and [23] also cope with the problem of RAT selection using game theory, but without considering the case of group mobility. Game theory is also used in [24] to ensure fair allocation of resources to mobile nodes after they perform a group handover.

The novelty of the work, presented in this paper, consists in the fact that it examines the stochastic situations whereby mobile users arrive simultaneously in groups and do not need to have any prior knowledge on the traffic load of other mobile users or any decisions taken by them [25]. The work does not assume either any involvement of base stations in broadcasting any kind of information to mobile users for RAT selection. In this paper, we propose two totally distributed algorithms based on congestion game theory to resolve the problem of RAT selection followed by network congestion in GVHO scenarios. A heuristic method and a hybrid learning scheme are also proposed to ensure fast convergence for groups of highly mobile nodes.

3. GAME THEORETIC MODEL

We consider a group of mobile users arriving at the same time to a zone covered by two wireless networks. Let n be the total number of mobile users in the group. We define by n_1 (resp. n_2) the number of mobile users connected to system s_1 (resp. s_2). For every mobile user, we consider that the utility function is equal to the throughput perceived by the mobile user. The throughput is determined by the number of mobile users as well as physical rate being used by the technology chosen. In this paper, we assume also that the mobile users choosing the same technology will receive the same throughput (the game is symmetric). This means that the utility function of any mobile user depends only on the number of users in the system. This type of non-cooperative game is a symmetric congestion game [26]. This type of game always results in at least one pure nash equilibrium whereby each player (mobile user) considers its chosen strategy to be the best under the given choices of other players. Therefore, at nash equilibrium, no user will profit from deviating its strategy unilaterally.

Let U_{s_k} be the utility function of a user connected to the system k. As the game is symmetric, a nash equilibrium $\left(n_1^*, n_2^*\right)$ is given by the two conditions:

- $U_{s_1}\left(n_1^*\right) \geq U_{s_2}\left(n_2^* + 1\right)$
- $U_{s_2}\left(n_2^*\right) \geq U_{s_1}\left(n_1^* + 1\right)$

The following conditions characterize the number of equilibria and sufficient conditions to have uniqueness of nash equilibrium.

Proposition 1. *For each group of n mobile users, let $\left(n_1^*, n_2^*\right)$ be the nash equilibrium. The non-cooperative game has one or two nash equilibrium* [23]. *Furthermore*

(1) If $U_{s_1}\left(n_1^*\right) > U_{s2}\left(n_2^* + 1\right)$ and $U_{s_2}\left(n_2^*\right) > U_{s1}\left(n_1^* + 1\right)$ then $\left(n_1^*, n_2^*\right)$ is the unique nash equilibrium.

(2) If $U_{s_1}\left(n_1^*\right) = U_{s2}\left(n_2^* + 1\right)$, then

- $U_{s_1}\left(n_1^* + 1\right) < U_{s2}\left(n_2^*\right)$
- $U_{s_1}\left(n_1^* - 1\right) > U_{s2}\left(n_2^* + 2\right)$

Then there are two nash equilibria $\left(n_1^*, n_2^*\right)$ and $\left(n_1^* - 1, n_2^* + 1\right)$.

(3) If $U_{s_1}\left(n_2^*\right) = U_{s2}\left(n_1^* + 1\right)$, then

- $U_{s_1}\left(n_2^* + 1\right) < U_{s2}\left(n_1^*\right)$
- $U_{s_1}\left(n_2^* - 1\right) > U_{s2}\left(n_1^* + 2\right)$

Then there are two nash equilibria $\left(n_1^*, n_2^*\right)$ and $\left(n_1^* + 1, n_2^* - 1\right)$.

3.1. The model

The game is defined as follows : G $= \{M, N, A_i, U_i\}_{i \in N}$

(1) M $= \{1 \ldots, m\}$ is the set of available networks in our scenario. We consider the coexistence between WiMAX and HSDPA systems (m = 2).

(2) N $= \{1 \ldots, n\}$ is the set of players (mobile users). Each mobile user is a player that has to pick one system network among the two available networks.

(3) $A_i = \{a_{i,1}, a_{i,2}, a_{i,3} \ldots, a_{i,m}\}_{i \in N}$: is the set of strategies of each player i. In our scenario, each player i has two strategies:

   - $A_{i,j} = a_{i,1} (i \in N), (j \in M)$ is a strategy of player i to choose WiMAX.
   - $A_{i,j} = a_{i,2} (i \in N), (j \in M)$ is a strategy of player i to choose HSDPA. Hence, $A_i = \{a_{i,1}, a_{i,2}\}_{i \in N}$ is the set of strategies of each player $i, A = \{A_1 \times A_2 \times A_3 \times \ldots \times A_N\}$ is the space of all profiles.

(4) n_w^t is the number of players that choose WiMAX at time t.

(5) n_h^t is the number of players that choose HSDPA at time t.

(6) U_i^t denotes the utility perceived by every player i at time t.

As the game is symmetric

$$U_i^t = \begin{cases} U_w\left(n_w^t\right), & \text{if } A_{i,j} = a_{i,1} \\ U_h\left(n_h^t\right), & \text{if } A_{i,j} = a_{i,2} \end{cases}$$

- $U_w\left(n_w^t\right)$ is the utility perceived by every player i in WiMAX at time t.
- $U_h\left(n_h^t\right)$ is The utility perceived by every player i in HSDPA at time t.

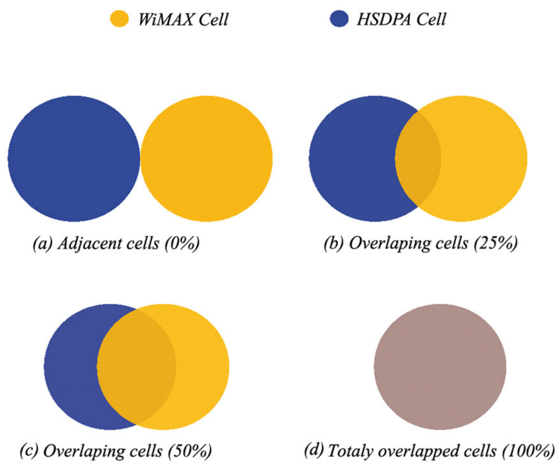

Figure 2. Joint coverage area. (a) Adjacent cells (0%), (b) overlapping cells (25%), (c) overlapping cells (50%), and (d) totally overlapped cells (100%).

3.2. The utility function

In WiMAX systems, the available throughput is gradually shared among mobile users, depending on the number of available sub-carriers [27]. Considering there is no inter cell interference, the available throughput capacity is C_w. The utility perceived by every player i in WiMAX at time t is given by

$$U_i^t = U_w\left(n_w^t\right) = \frac{C_w}{n_w^t}$$

In HSDPA systems, wireless resources are time shared in an opportunistic manner among the n mobile users. At time slot t, the base station algorithm schedules the user with the highest instantaneous rate relative to its average throughput [28]. C_h is the available throughput capacity; the mobile users are identical and the global throughput is a decreasing function of the number of mobile users present in the system that will be shared among these mobile users. The utility perceived by each player connected to the HSDPA system at time t is as follows:

$$U_i^t = U_h\left(n_w^t\right) = \frac{C_h}{n_h^t} G\left(n_h^t\right)$$

We denote by $G\left(n_h^t\right)$ the ratio of what the user receives from the base station as compared with a plain fair access scheduling. For Rayleigh fading [11], $G\left(n_h^t\right) = \sum_{i=1}^{n_h^t} \frac{1}{i}$. In this paper, we consider that the two technologies are totally overlapping as shown in Figure 2(d).

4. STOCHASTIC APPROXIMATION ALGORITHMS

In the present study, we choose two learning algorithms for non-cooperative environment.

4.1. Sastry algorithm

The first algorithm we consider is totally decentralized with incomplete information and based on a reinforcement of mixed strategies. The players are synchronized such that the decision of all players (playing a pure strategy) induces the utility perceived for each one. In [29], we can find the original algorithm on which we based our work. It has been proven that if this algorithm converges for a fixed number of players, it will always converge to a nash equilibrium. As the utility perceived by a player i at time t depends on his strategy as well as of the other mobiles, his utility function can be expressed as follows:

$$U_i^t = {}_{\{A_{i,j}=a_{i,1}\}} U_w\left(n_w^t\right) + {}_{\{A_{i,j}=a_{i,2}\}} U_h\left(n_h^t\right)$$

Then

$$U_i^t = \begin{cases} U_w\left(n_w^t\right), & \text{if } A_{i,j} = a_{i,1} \\ U_h\left(n_h^t\right), & \text{if } A_{i,j} = a_{i,2} \end{cases}$$

And

$$n = n_w^t + n_h^t$$

Given a set of strategies $A_i = \{a_{i,1}, a_{i,2}\}_{i \in N}$, each player i chooses at time t the pure strategy $A_{i,j} = a_{i,1}$ with probability $\pi_{i,a_{i,1}}^t$ (and conversely chooses the strategy $A_{i,j} = a_{i,2}$ with probability $(1 - \pi_{i,a_{i,1}}^t)$.

According to Sastry algorithm, all players i update their strategies using the rule described in the following formula:

$$\pi_{i,a_{i,1}}^{t+1} = \pi_{i,a_{i,1}}^t + b\left({}_{\{A_{i,j}=a_{i,1}\}} - \pi_{i,a_{i,1}}^t \right) \frac{U_i^t}{(Max(C_w, C_h))}$$

where $b \in [0, 1]$ is the learning rate. ${}_{\{A_{i,j}=a_{i,1}\}}$ is the characteristic function.

$${}_{\{A_{i,j}=a_{i,1}\}} = \begin{cases} 1, & \text{if } A_{i,j} = a_{i,1} \\ 0, & \text{if } A_{i,j} = a_{i,2} \end{cases}$$

The reinforcement learning calculations are carried out by each player until a threshold ϵ on consecutive results of probability π is not surpassed. Reaching individual convergence means that each user has no incentive on changing strategies, and there is no need to keep expending energy on calculations. The information about the number of mobile users (players) in group n is distributed to every user from a centralized entity.

Algorithm 1: Network selection with Sastry algorithm

Input: user parameters: C_w, C_h, n
$\epsilon = 10^{-5}$
Initialize $\pi^t_{i,a_{i,1}}$ as starting probability choice $A_{i,j} = a_{i,1}$ of each user i
For $t = 1$ to max-of-iterations
  For $i = 1$ to n
    Each user i take randomly current choice $A_{i,j} = a_{i,1}$ according to $\pi^t_{i,a_{i,1}}$ (conversely $A_{i,j} = a_{i,2}$ with probability $\left(1 - \pi^t_{i,a_{i,1}}\right)$).
  End For
  For $i = 1$ to n
    Each user i obtains a utility
    $U^t_i = \ _{\{A_{i,j}=a_{i,1}\}} U_w\left(n^t_w\right) + \ _{\{A_{i,j}=a_{i,2}\}} U_h\left(n^t_h\right)$
  End For
  For $i = 1$ to n
    Each user i updates his probability $\pi^t_{i,a_{i,1}}$ according to his choice:
    $\pi^{t+1}_{i,a_{i,1}} = \pi^t_{i,a_{i,1}} + b\left(\ _{\{A_{i,j}=a_{i,1}\}} - \pi^t_{i,a_{i,1}}\right) \frac{U^t_i}{(Max(C_w,C_h))}$
    If $\left|\pi^{t+1}_{i,a_{i,1}} - \pi^t_{i,a_{i,1}}\right| < \epsilon$ then
    user i has converged
    End
  End For
End For

4.2. Q-learning algorithm

The Q-learning algorithm [30] is used for the Markov decision process. It serves to determine an optimal strategy without knowing all the data (for the calculations by the dynamic programming). The rule of updating Q-learning is as follows:

$$Q(s_t, a_t) = Q(s_t, a_t) + \left[u^{t+1} + \gamma max_a Q(s_{t+1}, a) - Q(s_t, a_t)\right]$$

s_t and a_t are respectively the system state and the action chosen at time t. α is the learning rate, γ is the discount factor, u^{t+1} is the utility at time t+1, and Q is the estimation function action. At convergence, the function Q(s,a) will represent the maximum use of an action:

$$Q^*(s, a) = max_\pi Q^\pi(s, a)$$

And $\pi^* = argmax_\pi Q^*(s, a)$ is the optimal strategy. To apply Q-learning, we can use the following rule:

$$\pi^{t+1}_{i,a_{i,j}} = \frac{Q^{t+1}_{i,a_{i,j}}}{\sum_{j=1}^{m}\left(Q^{t+1}_{i,a_{i,j}}\right)}$$

Where $Q_{i,a_{i,j}}$ is the estimate of the value of action $a_{i,j}$ to player i, calculated as follows:

$$Q^{t+1}_{i,a_{i,j}} = Q^t_{i,a_{i,j}} + \alpha\left(\ _{\{A_{i,j}=a_{i,1}\}} U^t_i - Q^t_{i,a_{i,j}}\right)$$

Algorithm 2: Network selection with Q-learning algorithm

Input: user parameters: C_w, C_h, n
$\epsilon = 10^{-5}$
Initialize $\pi^t_{i,a_{i,1}}$ as starting probability choice $A_{i,j} = a_{i,1}$ of each user i
For $t = 1$ to max-of-iterations
  For $i = 1$ to n
    Each user i take randomly current choice $A_{i,j} = a_{i,1}$ according to $\pi^t_{i,a_{i,1}}$ (conversely $A_{i,j} = a_{i,2}$ with probability $\left(1 - \pi^t_{i,a_{i,1}}\right)$).
  End For
  For $i = 1$ to n
    Each user i obtains a utility estimation $Q^{t+1}_{i,a_{i,j}}$
    $Q^{t+1}_{i,a_{i,j}} = Q^t_{i,a_{i,j}} + \alpha\left(\ _{\{A_{i,j}=a_{i,1}\}} U^t_i - Q^t_{i,a_{i,j}}\right)$
  End For
  For $i = 1$ to n
    Each user i updates his probability π^{t+1}_i according to his choice:
    $\pi^{t+1}_{i,a_{i,1}} = \frac{Q^{t+1}_{i,a_{i,1}}}{\sum_{j=1}^{2}\left(Q^{t+1}_{i,a_{i,j}}\right)}$
    If $\left|\pi^{t+1}_{i,a_{i,1}} - \pi^t_{i,a_{i,1}}\right| < \epsilon$ then
    user i has converged
    End
  End For
End For

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5. RESULTS AND SIMULATION

5.1. Simulation scenario

In the first scenario, we consider that the two technologies are totally overlapping. We started the first simulation with a group of ten mobile users. Each mobile user in the group arrives at the same time to the totally overlapping zone. The maximum available throughput for each technology is fixed at C_w = 20 Mbps in WiMAX and C_h = 7.2 Mbps in HSDPA. We have picked an acceleration parameter b = 0.3 for the first algorithm and $\alpha = 0.03$ for the second, a convergence threshold $\epsilon = 10^{-5}$ and starting probability of each mobile user in the group at $\pi_{i,a_{i,1}} = 0.5$. All these parameters are summarized in the table below (Table I). The simulation results are obtained using MATLAB.

Table I. Simulation parameters.

Parameter	Value
C_w	20 Mbps
C_h	7.2 Mbps
b	0.3
α	0.03
n	10
$\pi_{i,a_{i,1}}$	0.5 $\forall(i \in N)$
ϵ	10^{-5}

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5.2. Results and analysis

Figure 3 depicts the evolution of mixed strategies of all mobile users and their convergence to pure strategies when they meet nash equilibrium after 800 iterations. After convergence, 60% of mobile users $(\pi_t^i = 1)$ take decision to switch to WiMAX and 40% of mobile users take decision to switch to HSDPA $(\pi_t^i = 0)$.

Figure 4 shows the average throughput achieved by mobile users in WiMAX and HSDPA. The condition of nash equilibrium is met after nearly 800 iterations and each user has no intention to change his strategies to improve his throughput. This result observed after 800 iterations is the best each user can achieve.

Figure 5 shows the evolution of mixed strategies of all mobile users and their convergence to pure strategies when they meet nash equilibrium after 2000 iterations. 60% of mobile users $(\pi_t^i = 1)$ take decision to switch to WiMAX and 40% of mobile users take decision to switch to HSDPA $(\pi_t^i = 0)$.

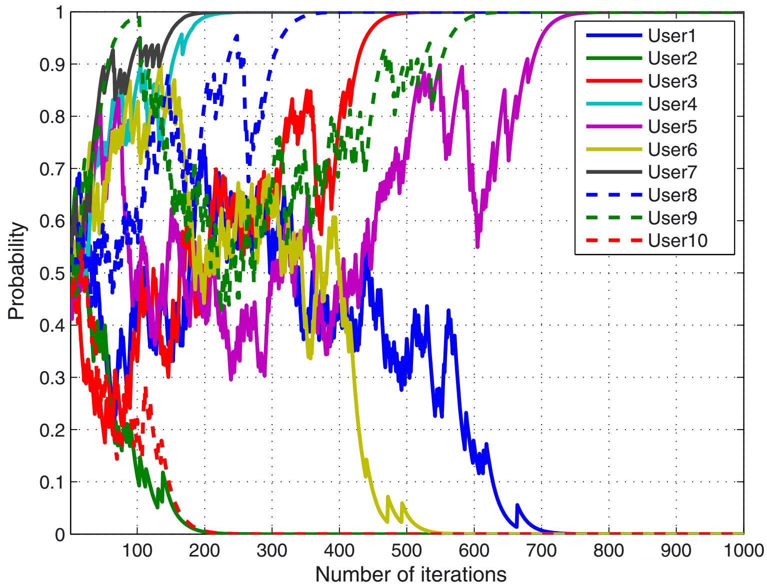

Figure 3. Evolution of mixed strategies in a group of ten mobile users with Sastry Algorithm.

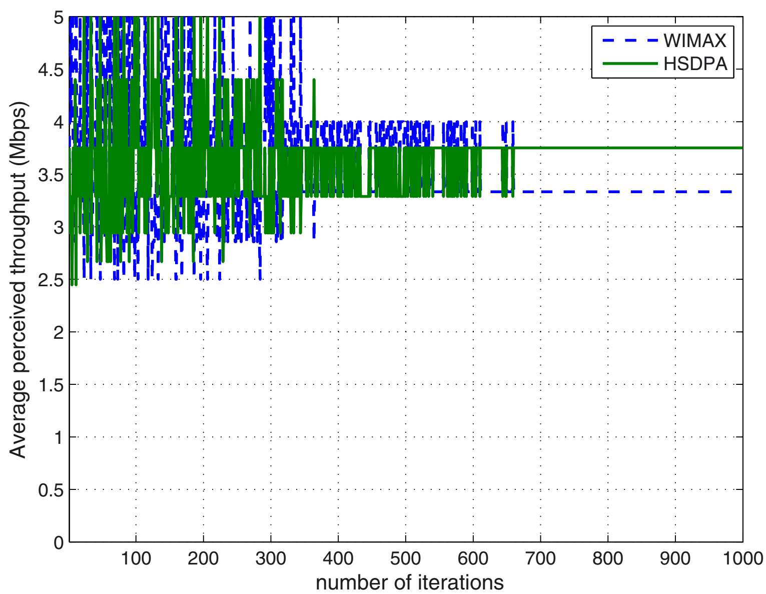

Figure 4. Evolution of average throughput of mobile users in Worldwide Interoperability for Microwave Access (WiMAX) and High-Speed Downlink Packet Access (HSDPA) using Sastry algorithm.

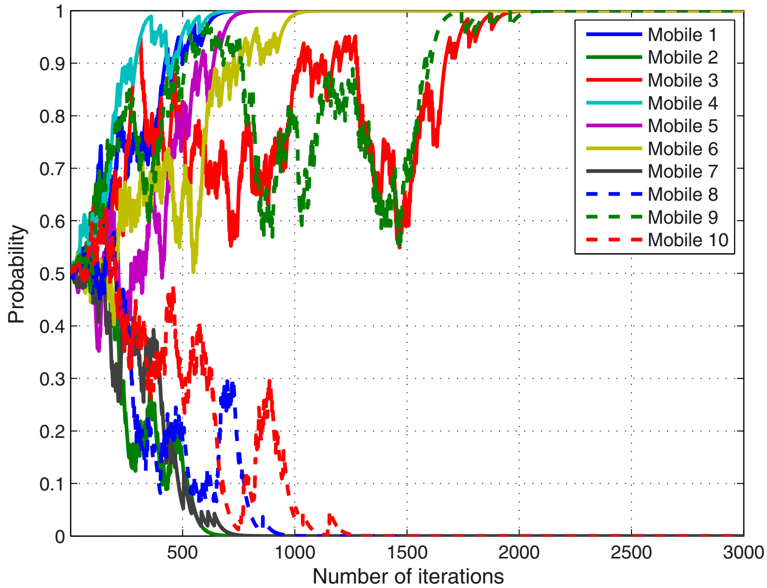

Figure 5. Evolution of mixed strategies in a group of ten mobile users using Q-learning algorithm.

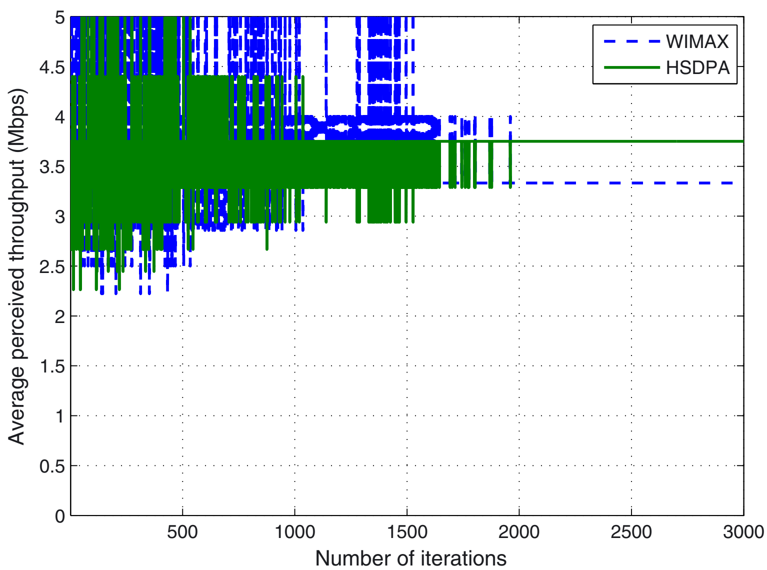

Figure 6. Evolution of estimated average throughput of mobiles in Worldwide Interoperability for Microwave Access (WiMAX) and High-Speed Downlink Packet Access (HSDPA) with Q-learning algorithm.

Figure 6 shows the average perceived throughput (utility) of mobiles in WiMAX and HSDPA. The condition of nash equilibrium has been meeting in iteration which is nearly 2000 and each user has no intention to change his strategies to improve his throughput. The result observed after the iteration 2000 is the best each user can achieve.

In the second scenario, we test with different numbers of mobile users in a group $n = \{5, 10, 15, 20, 30, 40, 50, 60, 70\}$. n represents the number of mobile users that come simultaneously in group to the totally overlapping zone.

In Figure 7, there are two main observations. The first one shows the average proportion of iterations to reach nash equilibrium for a different number of mobile users in a group using the Sastry and Q-learning algorithms. We notice that the larger the number of mobile users, the higher the number of iterations required till reaching nash equilibrium. The second observation shows that for a small number of mobile users in a group (less than

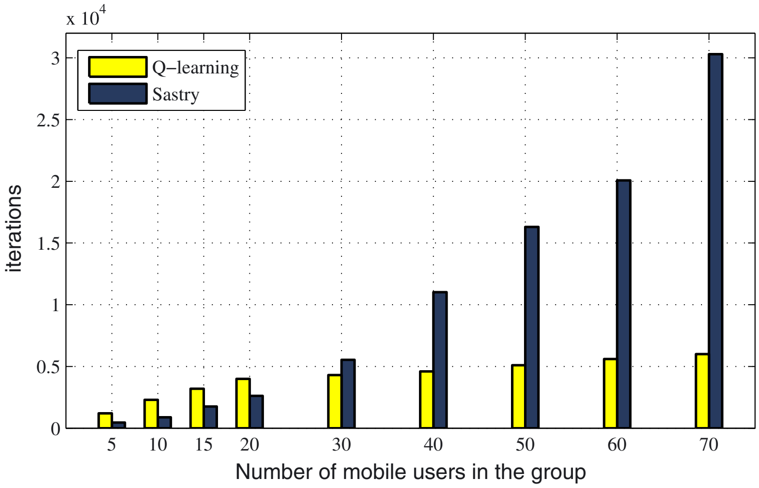

Figure 7. Evolution of the time of convergence along with increasing number of mobile users in the group.

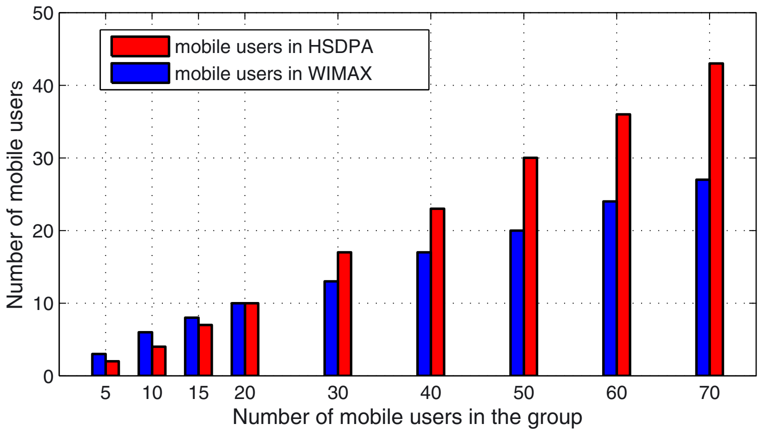

Figure 8. Evolution of mobile users' decisions to nash equilibrium for different group sizes. HSDPA, High-Speed Downlink Packet Access; WiMAX, Worldwide Interoperability for Microwave Access.

20 mobile users in the group), the Sastry algorithm converges rapidly compared with the Q-learning algorithm. The opposite happens if the number of mobile users in a group is more than 20. This is because of the different rules used in updating probability of mixed strategies in the two algorithms.

Figure 8 shows the total number of mobile users in each group and their distribution in both networks (WiMAX and HSDPA) after convergence to nash equilibrium. In short, the results show that after convergence of all mobile users, they do not have the same decisions (some of the mobile users choose WiMAX and the rest choose HSDPA). This process resolves the problem of network congestion. Although the capacity of WiMAX is larger than the capacity of HSDPA, a great portion of mobile users is gone to the HSDPA when there are many mobile users that arrive at the same time. This is because of the wide spread of HSDPA, which is the fact that this technology is initially intended for many mobile users, while WiMAX is limited to a few.

In order to evaluate our algorithms, we compare the results we have achieved with the Traditional Vertical Handover Algorithm, which is based on the available throughput capacity to take decisions.

Algorithm 3: Traditional vertical handover scheme: individual approach

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Mobile is receiving signal from more than one Base stations.
Begin
If ($C_w \geq C_h$)
    Mobile switch to WIMAX network
Else
    Mobile switch to HSDPA network
End If
End

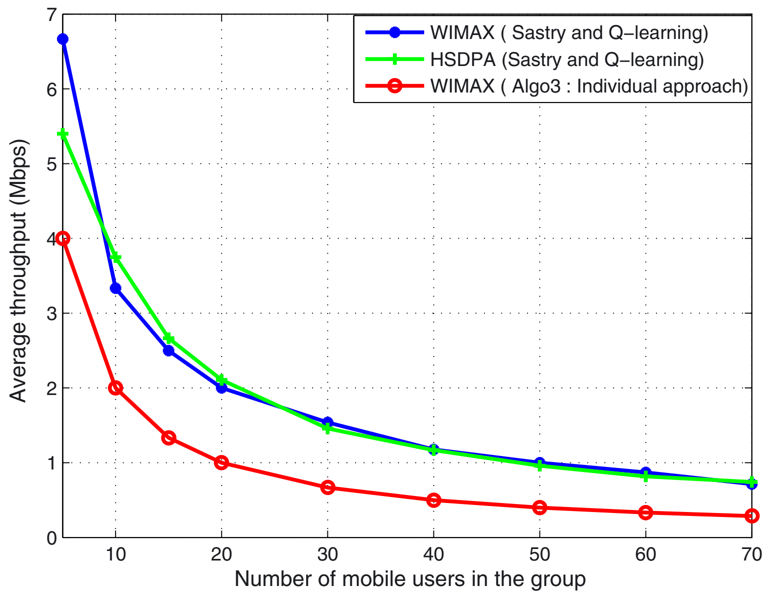

Figure 9. Throughput achieved in nash equilibrium for different sizes of mobile user groups.

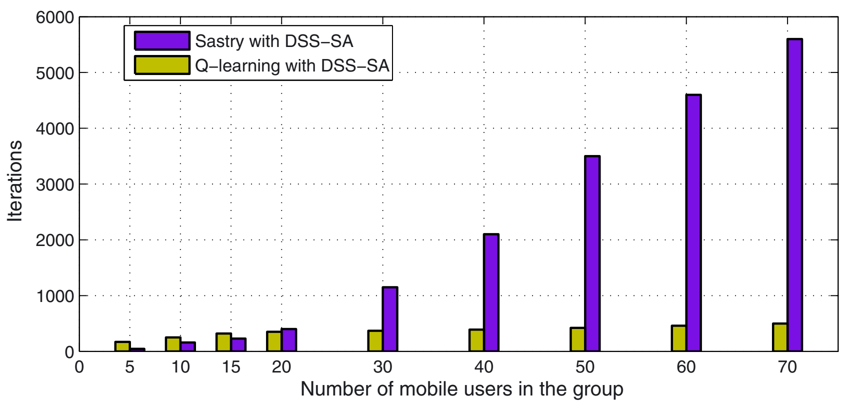

Figure 10. Evolution of the time of convergence along with increasing number of mobile users in the group. DSS-SA, decreasing step size-simulated annealing.

Figure 9 shows that choosing the best network (i.e., WiMAX presents the highest available network in this case) by all mobile users due to individual selection at the same time (i.e., represented by the red curve which shows the results of Algorithm 3) leads to dramatical degradation in the performance of mobile users. We also notice that the performance degrades further for larger groups of mobile users. However, our algorithms (Sastry and Q-learning) results (i.e., represented by the green and blue curves) show that the throughput achieved after convergence to nash equilibrium is decreasing in both networks, when more mobile users joint the group, but the performance achieved is higher than that achieved by the individual approach, and hence it is the best because mobile users choose different networks based on the decisions of each other. This results in solving the problem of network congestion and performance degradation because of the throughput achieved in nash equilibrium, which cannot be increased by changing strategies of each user.

6. FAST CONVERGENCE ADAPTED TO HIGH MOBILITY GROUPS

6.1. Accelerating convergence with heuristic method (DSS-SA)

In Section 4, we selected a fixed learning step ($b = 0,3$) for the sastry algorithm and ($\gamma = 0.03$) for the Q-learning algorithm during the convergence process. For fast convergence, we propose now a heuristic method for choosing the learning step of stochastic approximation algorithms. Although the learning step may need to be small enough to ensure convergence with high probability to a nash equilibrium, large values are suitable for reducing the convergence time of the algorithm. Consequently, we must find a good compromise between these two conflicting goals. DSS-SA is a heuristic method inspired from simulated annealing. We consider a cyclic decreasing step size as follows:

- $b = \frac{3}{((t mod(10))+1)}$;
  b : is the learning rate of Sastry Algorithm
- $\alpha = \frac{0.3}{((t mod(10))+1)}$;
  α : is the learning rate of Q-learning Algorithm.
  t: is the time.

Now, we simulate the second scenario in Section 5 to test the process of convergence.

Table II. Envisioned simulation scenario involving simultaneous mobility of groups of mobile users.

Time (iteration)	Event	Number of users in the group
500	arrival	5
1000	arrival	5
1500	arrival	5
2000	arrival	40
2500	arrival	10
3000	departure	55

As depicted in Figure 10, the heuristic method DSS-SA accelerates rapidly the time of convergence with excellent levels of convergence to the nash equilibrium (above 90%) in both Sastry and Q-learning algorithms. This is obvious when we compare the results in Figure 7 with those of Figure 10, in which we show that for small groups of mobile users (i.e., less than 20 mobile users in a group), the Sastry algorithm with DSS-SA converges rapidly compared with Q-learning. The opposite happens if the number of mobile users in a group exceeds 20.

6.2. Hybrid learning with decreasing step size-simulated annealing

6.2.1. Hybrid learning algorithm.

In order to adapt the convergence time to the case of a high mobility group (i.e., departures and arrivals of groups) and based on the results and analysis of the previous section, we propose now a hybrid learning algorithm to take advantage of fast convergence time of the two learning algorithms with DSS-SA heuristic. To illustrate the improvement expected by the hybrid learning versus Sastry with DSS-SA and Q-learning with DSS-SA, we performed a test in which the algorithm has to be run upon every arrival or departure of a group of mobile users in an overlapping zone as described in Section 5. The information about the new number of mobiles in an overlapped zone n is distributed to every user from a centralized entity at each departure or arrival.

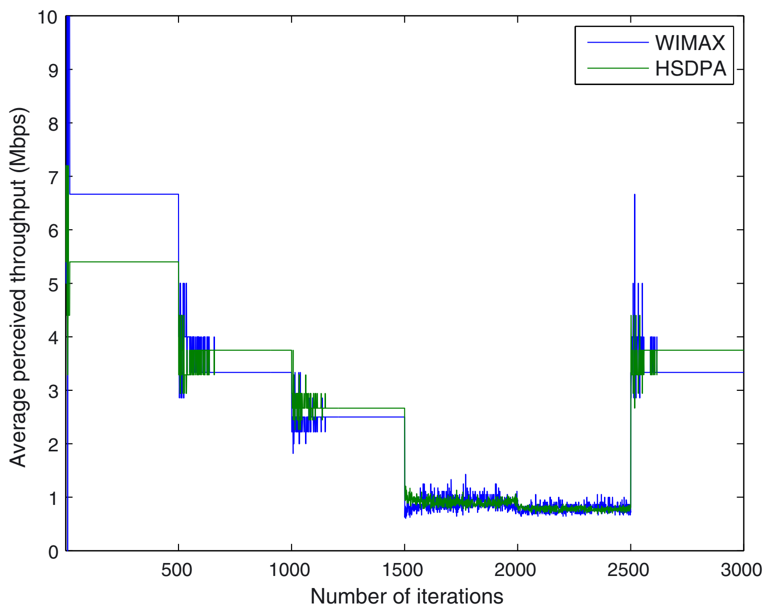

Figure 11. Evolution of average throughput of mobile users in Worldwide Interoperability for Microwave Access (WiMAX) and High-Speed Downlink Packet Access (HSDPA) with Sastry decreasing step size-simulated annealing (DSS-SA).

Algorithm 4: Hybrid learning with DSS-SA
At each departure or arrival do : get (n)
If ($n \geq 20$)
execute Q-learning with DSS-SA
Else
execute Sastry with DSS-SA
EndIf

6.2.2. Simulation and results.

In the simulations, we consider groups of mobile users with high mobility features. The envisioned scenario is described in Table II.

Figure 11 shows the average throughput achieved by mobiles users connecting to WiMAX and HSDPA when using the Sastry DSS-SA algorithm. As per the envisioned scenario, at each 500 iterations, there is a departure or

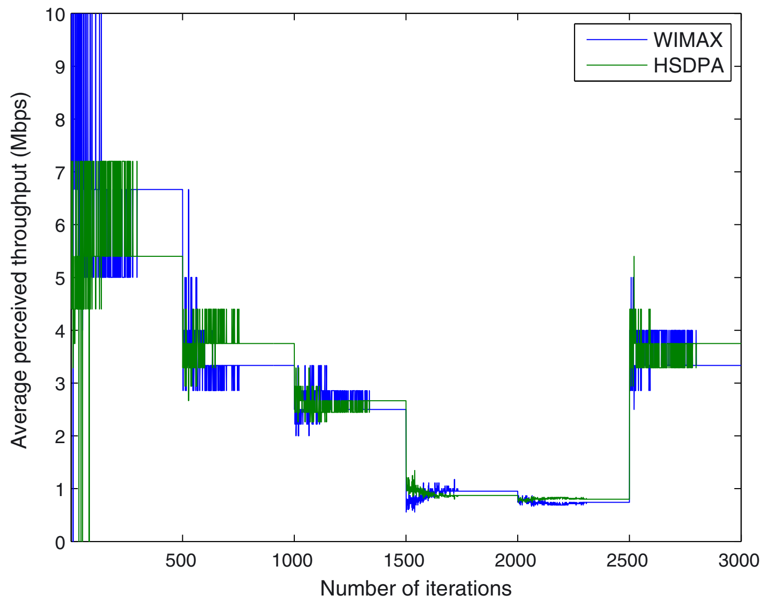

Figure 12. Evolution of average throughput of mobile users in Worldwide Interoperability for Microwave Access (WiMAX) and High-Speed Downlink Packet Access (HSDPA) with Q-learning decreasing step size-simulated annealing (DSS-SA).

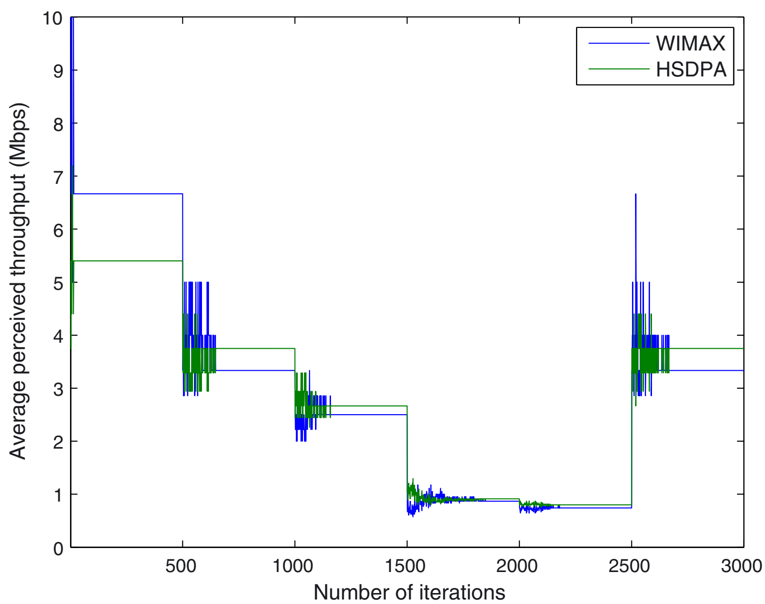

Figure 13. Evolution of average throughput of mobile users in Worldwide Interoperability for Microwave Access (WiMAX) and High-Speed Downlink Packet Access (HSDPA) with hybrid learning.

arrival of a group of mobile users. Convergence to a new nash equilibrium then becomes needed. The time of convergence of Sastry algorithm with DSS-SA is much faster when the number of mobile users is small (i.e., iterations 0,500,1000,1500, and 2500). All mobile users converge in less than 300 iterations. However, we notice no convergence when the number of mobile users is large (i.e., iterations 1500 and 2000).

Figure 12 plots the average throughput achieved by mobile users connecting to both WiMAX and HSDPA when the Q- learning DSS-SA algorithm is in use. As explained earlier, at each 500 iteration, a group of mobile users join or leave the overlapping zone, pushing for the need of a new nash equilibrium. From the figure, we notice that the time of convergence of the Q-learning algorithm with DSS-SA is much faster when the number of mobile users is large (i.e., iterations 1500 and 2000) as all mobile users converge in less than 300 iterations. However, we notice a low time convergence when the number of mobiles is low (iterations 0,500,1000,1500, and 2500).

Figure 13 shows the average throughput achieved by mobile users in the case of the hybrid learning algorithm. From the figure, the hybrid learning algorithm exhibits the best performance in terms of speed to converge to nash equilibrium and that is regardless of the size of the group of mobile users joining or leaving the network.

7. CONCLUSION

In this paper, we have studied the problem of congestion network in GVHO scenarios when multiple mobile nodes perform handover at the same time. GVHO frequently occurs in the context of group mobility. Because each mobile node selects individually the best network without taking into consideration the other nodes decisions, it is likely that individual selection will result in network congestion and the degradation of network utility. Two learning algorithms are proposed allowing to each mobile in the group to reach nash equilibrium with no information being broadcast by the base stations. This results in solving the problem of network congestion and performance degradation in GVHO scenarios. Simulation results validate the algorithms and show their robustness in converging fast to nash equilibrium for different numbers of mobile users. Finally, we proposed a heuristic method called Decreasing Step Size (DSS-SA) inspired from simulated annealing and incorporated in a hybrid learning algorithm to speed up convergence time and maintain efficient solutions with excellent levels of convergence to the nash equilibrium (above 90%). The last simulation results show the suitability of our hybrid algorithm with different group mobility scenarios. It is all the hope of the authors that the presented results open the way to several interesting future research works, such as the implementation of our hybrid algorithm with DSS-SA on mobile devices.

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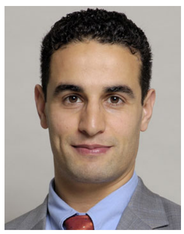

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