Mobility Analysis for Passive Reservations in Vehicular Cellular Networks Based on Dynamic Programming and Roads Compression

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Abstract— **The employment of an appropriate Bandwidth Management Scheme (BMS) is needed in wireless networking, given that the main desire of end-users is to take advantage of satisfactory services, in terms of Quality of Service (QoS), especially when a particular charge is paid to meet the requirement. In this paper we are interested in investigating how the continuity of services can be guaranteed in QoS networks, when users move from a cell to another one, under an infrastructure cellular coverage. The only way to face this issue is represented by the employment of in-advance bandwidth reservations, although it leads the system to waste bandwidth resources, since they are not used until the mobile host enters the coverage cell where the passive request has been made. A new scheme for predicting user movements is proposed, taking the advantage of the dynamic programming approach, that is able to reduce the number of possible roads to be considered and thereby increasing/decreasing the accuracy/redundancy of the proposed model. Several simulation runs have been carried out in order to assess the effectiveness of the proposed idea.**

Keywords- Mobility prediction, Pattern, Markov, Citymob, Passive, Resource, Reservation, Distributed, Bandwidth, Hand-over management, Mobile host, Quality of Service, QoS, Optimization, Wireless Networks.

I. INTRODUCTION

With the rapid growth of Internet of Things (IoT) and mobile communications, the need for QoS guarantees has become of primary importance, especially when hand-over events occur by Mobile Hosts (MHs) changing coverage areas during their active sessions; they may find scarce resource availability in new locations and the current active connections can be dropped. To the best of our knowledge, the only way to ensure QoS and service continuity to mobile users consists of making a bandwidth reservation over all the cells that a MH will visit during its active connection. There are many protocols able to ensure early reservations like Next Step In Signaling (NSIS) [1], Dynamic ReSerVation Protocol (DSRVP) [2] and Mobile ReSerVation Protocol (MRSVP) [3], but a prediction scheme is mandatory in order to know which coverage cells a user will probably visit during its Call Life Time (CLT). On the basis of previous works [4], [5], we considered the MRSVP, which gives the possibility to exchange the right communication messages among the predicted coverage cells, achieving the needed passive amount of bandwidth in the cells where the MH will probably hand-in. The same Markov model has been considered, but an optimization on the number of chain states is now proposed: in the previous contributions, only one hand-over direction has been considered for the hand-off event toward a next cell, without considering the roads topology that characterize MH movements. Given that the number of chain states could be very large if all the roads that lead to another cell are considered, an optimization scheme is proposed. In particular, the dynamic programming approach is considered [6], having the possibility to choose the right number of states for the Markov model, taking into account the morphology of the considered geographical region. An approximation has been introduced and the associated error has been minimized. Clearly, in order to implement and realize this kind of prediction, a real network operator has to analyse users' mobility, through a statistical treatment. In our case, without access to real data about MH movements, we employed the Citymob for Roadmaps (C4R) mobility generator [7], in order to appreciate prediction performance when mobility traces are extracted from real roadmaps of different countries (the mobility model has a heavy impact on the obtained results, that may be unsuitable if the adopted mobility model is unrealistic). The integration between the Markov process and the dynamic programming approach leads to a new distributed prediction scheme, called Dynamic Markov Prediction Algorithm (DMPA), tested through extensive simulation studies. The rest of the paper is organized as follows: section II gives an overview of the existing related work, section III gives a detailed description of the proposed scheme, by considering the environment and the solution. Section IV shows our simulation results, then section V concludes the paper.

II. LITERATURE OVERVIEW

Mobility and resource management are critical for providing QoS guarantees in wireless networks, so it is very important to accurately describe mobility patterns of MHs in wireless cells, especially when a prediction approach is needed. In [8] the Mobility-Dependent Predictive Resource Reservation (MDPRR) scheme is proposed, that is able to provide flexible usage of limited resource in mobile multimedia wireless networks. Each cell is divided into non-hand-off, pre-hand-off and hand-off zones, so that bandwidth is reserved in the target/sub-target cell as mobile stations move into the pre-hand-off zone. An admission control scheme is also considered to further guarantee the QoS of real-time traffic as, for example, Voice over IP, as proposed in [9] and [10]. The Fixed Bandwidth Reservation (FBR) scheme [11] can improve the dropping probability of hand-off connections by reserving a fixed number of channels exclusively for hand-off connections. The drawback of this scheme is that the reserved bandwidth is often wasted in the hot spot area. In [12] the authors optimize some system parameters in terms of Call Dropping Probabilities (CDPs) and Call Blocking Probabilities (CBPs) introducing a prediction algorithm based on data mining approaches, in order to implement a distributed Call Admission Control (CAC) scheme, considering also the throttle flag as indication of the usage of each cell. Through estimation of MHs trajectory and arrival/departure times in [13], a group of future cells is determined: it constitutes the most likely cluster into which a terminal will move. Two passive reservation techniques are proposed in [14], exploiting Wiener prediction and time series theory, making in-advance reservations under non-Poisson and/or non stationary arrival processes, arbitrary distributed call and channel holding time and arbitrary per-call resource demands. In [15] the authors give a contribution in WLAN infrastructure planning, basing their decisions on mobility prediction: they propose a new method for feature extraction with a novel neural network classifier based on a hidden genetic algorithm, reaching an acceptable prediction accuracy. In previous works, like [16] and [17], a prediction technique based on the Cell Stay Time (CST) evaluation of a mobile user is proposed. A formula that relates cell coverage radius and speed is calculated and resource reservation techniques have been proposed, so it is possible to evaluate the number of coverage cells that users will visit during their CLT. To the best of our knowledge, all the literature is focused on the prediction of a single next cell, without the guarantee of service continuity during the whole flow lifetime. In addition, they do not take into account the geographical morphology of the considered region, in terms of roads, that heavily influences driving styles and mobility patterns in terms of cell sequences. In this work, instead, the DMPA algorithm is proposed: it provides a distributed set of Markovian predictors, each one optimized in terms of number of states and local road topology coverage. With respect to previous works [4], [5], [17], [18], DMPA optimizes the number of states for each chain, taking into account the particular roads structure. In this way, the number of states for each cell is variable and it strictly depends on the possible MH movements in the considered region. As mentioned before, the number of states of each chain is adequately chosen, minimizing the error committed during the approximation. Each Markovian chain is trained by taking into account local trajectories (belonging to the associated coverage cell); each predictor is specialized for the specific coverage area, with different traffic densities, in terms of roads, road populations, moving directions and so on; the considered signaling protocol has been integrated with Markov chains in order to realize a complete prediction scheme. Although the proposed idea is based on MRSVP and Markovian processes, it is suitable for any other signaling protocol and/or (un)conventional prediction approach. The effectiveness of DMPA has been also verified in terms of accuracy error, by considering different movement traces of MHs and the length of learning observations.

III. Problem Statement, System Characterization and Proposed Idea

In this section, the proposed idea is completely described. It must be noted that the proposed idea does not depend on the employed protocol: for example, it can be one of those used or described in [1], [3]. As stated before, we chose the MRSVP [1], with which one reservation is made by a user on the current coverage cell (active reservation), while passive ones are made on the predicted remote cells. When hand-overs events have to be managed in an adequate manner, MRSVP can be employed, handling users mobility and offering guaranteed services, giving the chance to mobile users to make reservation requests over more than one cell, by their proxy agents. For more details about MRSVP to see [3]. In our work, we considered that a MRSVP session starts with the active service request performed by a MH u on its active cell c_t; if there are no free channels in c_t, the call is refused, else c_t applies the results obtained in [3], [16] to evaluate the number of predicted hand-over events. If no hand-over events are predicted (the CST>>CLT), then the call is accepted (u will visit only the current cell c_t). Otherwise the proposed DMPA is used to predict the neighbor cell $nc \in Adj(c_t)$, where $Adj(c_t)$ is the set of neighbors of cell $c_t \in C$ and $||Adj(c_t)||=n$, where n is the number of possible hand-over directions. We considered a generic Geographical Region GR covered by a number of cells equals to c. Let C be the set of coverage cells of the considered wireless network, $C=\{c_1,c_2,\ldots,c_c\}$ with $||C||=c$. For each cell $c_t \in C$, with a coverage radius r_t, a set of neighboring cells $Adj(c_t)$ can be defined, on the basis of network topology and cell adjacencies. A circular coverage cell can be approached with a n-edge regular polygon and, considering n=6, coverage cells are represented by regular hexagonal areas, as approached in [18]. In addition, a set S_{ho} of n movement directions $d_1 \ldots d_n$ can be introduced, where $d_j=\underline{\theta}\cdot(2\cdot j-1)/2$ *rad.*, $\underline{\theta}=2\pi/n$ *rad.* and $j=1..n$ (it represents the j-*th* side of the hexagon), so $S_{ho}=\{d_1,\ldots,d_n\}$, $||S_{ho}||=n$. In this work $||Adj(c_t)||=||S_{ho}||=6$, $\forall\, c_t \in C$.

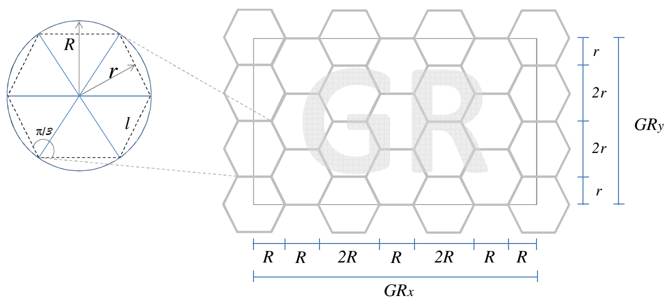

Figure 1. Hexagonal approximation (n=6) and GR coverage.

Differently from [18], we will show how considering only $n=6$ (without further considering additional angles), the model suffers a certain error in prediction making, so more granularity is required, without exceeding in computational complexity, in order to adapt the local approximation model to the morphology of the covered territory. Let $GR_x{\cdot}GR_y$ be the area of the considered region GR; without loss of generality, let us assume that $r_t=R\ \forall\ c_t \in C$ so, referring to fig. 1, note how each circular region of radius R, can be approximated by an hexagon, with an apothem r equals to $R{\cdot}(\sqrt{3}/2)$ and $l=R$. So, given the area to be covered as $GR_x{\cdot}GR_y$ and hypothesizing that $R<<GR_x$, $R<<GR_y$ a lower bound for c, c_{low}, is given by:

$$c_{low} = \left\lceil 2\cdot\frac{GR_x\cdot GR_y}{6\cdot R\cdot r}\right\rceil \tag{1}$$

because the total area is divided by the area of a single hexagonal coverage cell. The expression of c_{low} represents a lower bound because the shape of each cell cannot fit exactly the considered area, as shown in fig. 1, so additional cells are needed. In particular, referring to fig. 1 and respecting the considered geometry, an upper bound for the number of needed cells can be assumed to be $c_{high}=k_x{\cdot}k_y$, where:

$$R + k_x\cdot 3R \geq GR_x \tag{2}$$

$$r + k_y\cdot 2r \geq GR_y. \tag{3}$$

Evaluating the expressions for k_x and k_y and rounding to the next integer value, we obtain that:

$$c_{high} = \left(\left\lceil\frac{GR_x - R}{3R}\right\rceil + 1\right)\cdot\left(\left\lceil\frac{GR_y - \sqrt{\frac{3}{2}}R}{\sqrt{6}\cdot R}\right\rceil + 1\right) \tag{4}$$

The same treatment can also be made for a circular geographical region GR with a shape of radius GR_R. The expression of c_{low} becomes:

$$c_{low} = \left\lceil 2\cdot\frac{\pi\cdot GR_R^{\ 2}}{6\cdot R\cdot r}\right\rceil \tag{5}$$

while for c_{high} the expression becomes:

$$c_{high} = 3\cdot k_R\cdot(k_R - 1) + 1 \tag{6}$$

as concluded in [17], [18], where k_R is defined as:

$$k_R = \left\lceil\frac{GR_R - \sqrt{\frac{3}{2}}R}{\sqrt{6}\cdot R}\right\rceil + 1. \tag{7}$$

In previous works [4], [5], [17], [18] we did not differentiate the model for different road densities. In particular, referring to fig. 2, we can observe how a cell $c_t \in C$, based on the value of r_t, can manage a different number of roads. Let us consider two cells c_1, $c_2 \in C$, which cover real geographical areas (two locations of a city in south Italy are considered). We can immediately observe how the number of possible hand-over roads for c_2 (three sides on a total of six have only one possible direction for hand-over) is less than the one for c_1 (the crosses on the hexagonal sides represent some of the possible hand-in/hand-out points, i.e. intersections among roads and cell sides).

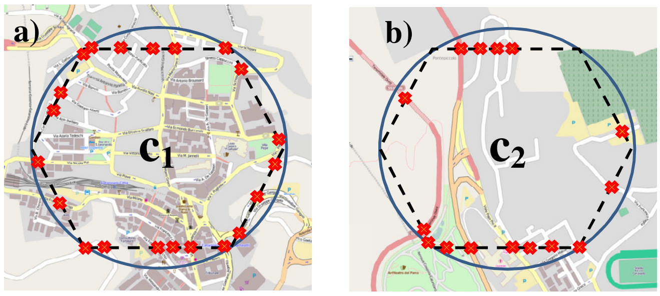

Figure 2. Different road densities for different coverage cells c_1 and c_2.

The main idea is to extend the number of states of the model in order to take into account all the possible crossing directions; on the other side, the complexity of the proposed model cannot be increased indefinitely, so a right trade-off should be found, aggregating, when possible, roads information belonging to users mobility. At this aim, we considered the approach of [6], in which an input sequence of a certain size has been divided into a lower number of sub-sequences, each one represented by the average value; the obtained partitioning minimizes the error due the approximation process. Let us hypothesize that each coverage node (Access Point, Base Station, etc.) is able to recognize the direction on which a MH enters or leaves the cell (many Direction-of-Arrival (DoA) algorithms are present in the literature, depending on the adopted technology). So, referring to a generic coverage cell $c_t \in C$, for each $d_j \in S_{ho}$ we can define a set of roads $RD_{dj} = \{rd_{dj1}, rd_{dj2}, \ldots, rd_{djJ}\}$ where $rd_{djk} \in [0,2\pi]$, $k=1,\ldots,dj_J$.

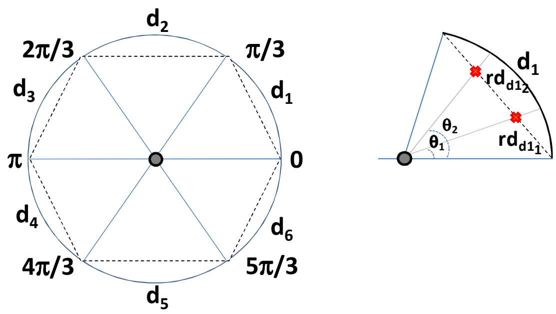

Figure 3. Cell directions subdivision and intersection degrees determination.

From fig. 3 it can be seen how, for $n=6$, for each $d_j \in S_{ho}$ which represents the "average" direction associated to side j, the lower and upper bounds can be determined as $[d_j-\pi/6, d_j+\pi/6)$, so each $rd_{djk} \in RD_{dj}$ belongs to that interval. Figure 3 shows, on the right, how the angles of road intersections can be determined. Given the sequence of roads/angles $RD_{dj} = \{rd_{dj1}, rd_{dj2}, \ldots, rd_{djJ}\}$, with $||RD_{dj}||=J$ and a compression factor

λ (with $\lambda<J$), the set RD_{dj} has to be divided into λ sub-sequences and each of them has to be replaced with its average value. We followed the approach of [6], which is able to solve a subclass of the run-length coding scheme in polynomial time, using a dynamic programming approach. In particular, each $rd_{djk} \in RD_{dj}$ is associated to the terminal nodes of the base level of a Compact Binary Tree (CBT), composed by $2 \cdot J-1$ nodes, assuming that $J=2^{l_J}$. The CBT is represented by an array of the form $T_{dj}=[t_1, t_2, \ldots, t_{2J-1}]$, where each element is associated to a node: the last J elements store the values of RD_{dj}, while each t_k, with $k<J$, has two children t_{2k} and t_{2k+1} and 2^{h_k} descendents, with $h_k=l_J - \lfloor \log_2 k \rfloor$, which represents a subsequence S_k of the input sequence:

$$S_k = \{t_h \mid t_h = rd_{dj_{h-J}} \ \ and \ \ k \cdot 2^{h_k} \le h < (k+1) \cdot 2^{h_k}\}. \quad (8)$$

In addition $t_k=(t_{2k} + t_{2k+1})/2=\mu_k$. Considering c_1 and c_2 and directions d_1 and d_6 respectively, fig. 4 shows the CBTs.

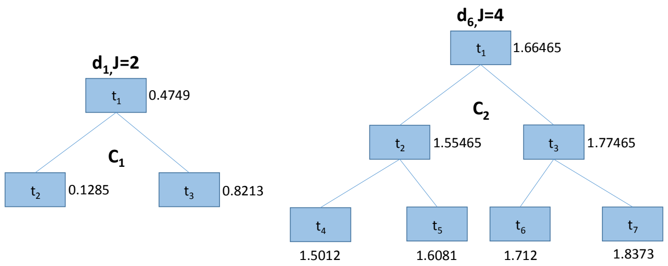

Figure 4. CBTs for two different directions.

The related arrays are: $RD_{d1}=\{rd_{d11}, rd_{d12}\}=\{0.1285, 0.8213\}$, $T_{d1}=[0.4749, 0.1285, 0.8213]$, $RD_{d6}=\{rd_{d61}, rd_{d62}, rd_{d63}, rd_{d64}, rd_{d65}, rd_{d66}\}=\{1.5012, 1.6081, 1.712, 1.8373\}$, $T_{d6}=[1.664651, 1.55465, 1.77465, 1.5012, 1.6081, 1.712, 1.8373]$. With the approach of [24], the problem is solved by minimizing the quantity $ERR(k,\lambda)$, representing the error of compressing the roads subsequence S_k using λ values:

$$ERR(k,\lambda)=\begin{cases} \varepsilon_k & \lambda=1 \\ \min\limits_{1\le p<\lambda}[ERR(2k,p)+ERR(2k+1,\lambda-p)] & \lambda>1 \\ 0 & \lambda>2^{h_k} \end{cases} \quad (9)$$

where ε_k is the mean square error committed with the compression of the roads subsequence S_k with a single value:

$$\varepsilon_k = \frac{1}{\| S_k \|} \sum_{t_h \in S_k} (\mu_k - rd_{dj_h})^2 \quad (10)$$

For more details about dynamic programming and run-length coding approach, please refer to [6].

At this point, for each cell $c_t \in C$, an array $\Lambda_t=[\lambda^t_1, \ldots \lambda^t_n]$ (with $n=6$ in our case) can be defined, where each λ^t_j indicates the best compression factor for cell c_t associated to RD_{dj} on direction $d_j \in S_{ho}$ and $1 \le \lambda^t_j \le \|RD_{dj}\|$. For each λ^t_j, a partition vector $M^t_j = [\mu^t_{j1}, \ldots, \mu^t_{j\lambda j}]$ represents the compressed sequence, for the j-th side of cell c_t; each element μ^t_{jk} has an associated partition range $p^t_{\mu jk}$, belonging to the j-th Partition Set PS^t_j, defined as:

$$p^t_{\mu_{jk}} = \begin{cases} [d_j - \frac{\pi}{6}, \ \ \mu^t_{j_k} + \frac{(\mu^t_{j_{k+1}} - \mu^t_{j_k})}{2}] & k=1 \\ [\mu^t_{j_k} - \frac{(\mu^t_{j_k} - \mu^t_{j_{k-1}})}{2}, \ \ \mu^t_{j_k} + \frac{(\mu^t_{j_{k+1}} - \mu^t_{j_k})}{2}] & 1<k<\lambda_j \\ [\mu^t_{j_k} - \frac{(\mu^t_{j_k} - \mu^t_{j_{k-1}})}{2}, \ \ d_j - \frac{\pi}{6}] & k=\lambda_j \end{cases} \quad (11)$$

In DMPA, a Finite State Markov Chain is considered: the set of states is not only related to the number of possible hand-over directions, but it considers also the number of roads of the covered region. Given vectors $\boldsymbol{M^t}$ and $\boldsymbol{PS^t}$, defined in previous section, with $\|\boldsymbol{PS^t}\|=\|\boldsymbol{M^t}\|=n$, the idea is to associate one state of the Markovian model to each partition subset, representing a compressed set of roads, for each side of c_t. A Markov chain (fig. 5) can be associated to a cell c_t:

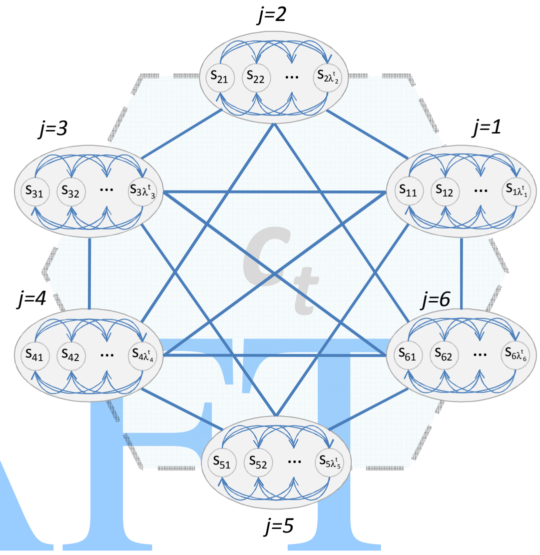

Fig. 5. An example of Markovian cell modeling.

A road rd_{djq}, that intercepts cell c_t on side j, is said to belong to state s_{jk} if:

$$rd_{d_{jq}} \in p^t_{\mu_{jk}}. \quad (12)$$

In this paper we are not focusing on the definition of a Markovian model, we want to optimize, instead, the number of states of the model. So, without entering in the particulars of the Markovian theory, we can write that the DMPA Markov Chain, related to the t-th (indicated with DMC^t), can be described by three terms: Π^t, σ^t and ST^t. For the details about the introduced triplet and their evaluation, please refer to [5]. Figure 6 illustrates how a distributed set of MCs $\boldsymbol{MC}=\{MC^t, 1\le t\le c\}$ can be used to model the whole cellular system. In order to be admitted into the system, each mobile host makes a reservation request to the current coverage cell (active reservation) and to the predicted ones (passive reservations). This is made by employing the native signaling packets of the MRSVP. If at least one cell sends a negative answer (no available bandwidth), the call is refused, then the MH will try again later. In the next section, more details about our simulation setups and results will be given.

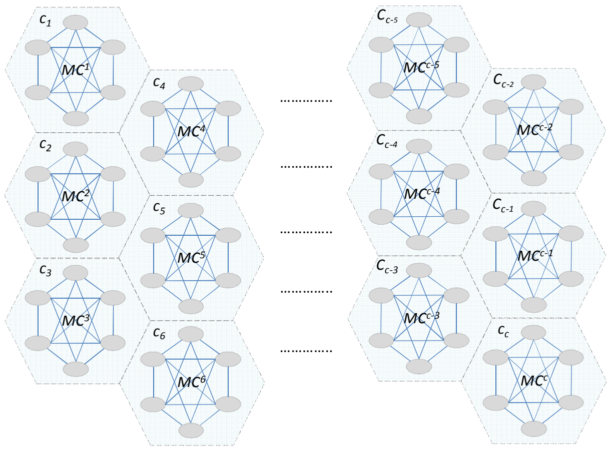

Fig. 6. An example of wireless cellular system modeled through MCs.

IV. PERFORMANCE EVALUATION

In order to evaluate the proposed integration in terms of average prediction error, Call Dropping Probability (CDP) and Call Blocking Probability (CBP), we considered real mobile environments: Citymob mobility generator [7] and the C4R GUI have been considered, because they give the opportunity of obtaining mobility traces from real maps. In particular, we used maps of some European cities (about 1 km^2 for each scenario), over which a set of coverage cells (all with the same coverage radius R) has been considered (r_t=R, $\forall$ $c_t \in C$) and $R \in [50, 250]$ meters. Square maps have been considered and fig. 7 shows the obtained values of upper and lower bounds (eq. 1 and eq. 4), independently on the considered road topology.

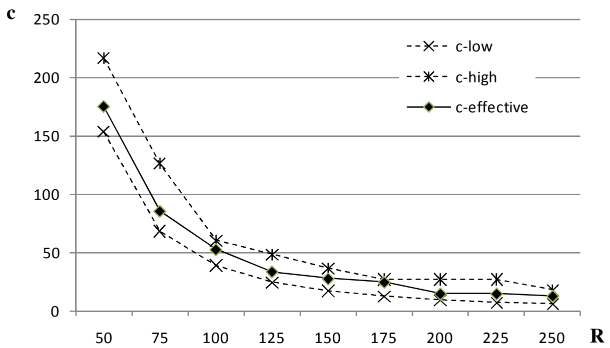

Fig. 7. Number of necessary cells for different coverage radius.

It is shown that, when the coverage is set-up, the effective number of employed cells always respects the obtained bounds. As stated before, different cities have been considered and, for all of them, obtained results are comparable: without loss of generality, we show the obtained curves for the city of London; fig. 8 illustrates the obtained coverage for R=110m and GR_x=GR_y≅1000m; in this case c_{low}=31, c_{high}=54 and c=42. Once the topology of GR has been determined, as well as the coverage map, the compression algorithm needs to be executed for all cells. In order to choose the right number of partitions for each c_t and direction, a compression factor cf_t is chosen, so:

$$\lambda_j^t = \begin{cases} 0 & \text{if } \|RD_{dj}\|=0 \\ 2^{\left[\log_2 \left\lceil (1-cf_t)\cdot\|RD_{dj}\|_t \right\rceil\right]} & \text{if } \|RDdj\|\neq 0 \text{ and } (1-cf_t)\cdot\| RDdj \|_t >1 \\ 1 & \text{else} \end{cases} \quad (13)$$

where the [.] operator indicates the integer part.

For each cell c_t, a total of twenty slots (ns^t = 20) has been considered and each reservation occupies a single slot in each cell (active or passive). Only for example, Table I resumes the values of $\|RD_{dj}\|$ and λ_j^t for three cells (c_{10}, c_{18}, c_{33}) as illustrated in fig. 9, while table II indicates the obtained $\boldsymbol{\Lambda_t}$ sets for different values of cf_t.

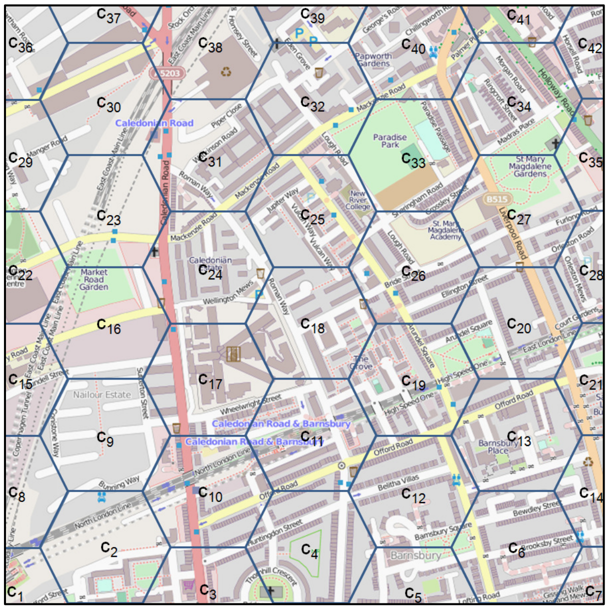

Fig. 8. The set of 42 cells used to cover the considered region.

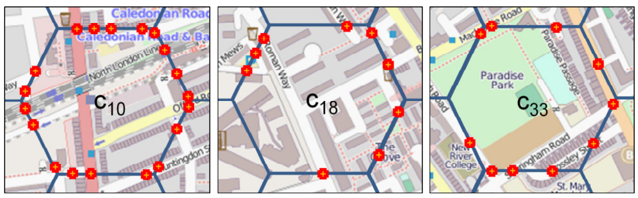

Fig. 9. Road sets for some cells of the considered network.

In order to better understand how the different road sets are partitioned, cell c_{10} has been considered graphically, fig. 10, for different compression factor values (0.2, 0.4, 0.6 and 0.8).

TABLE I. NUMBER OF ROADS FOR EACH DIRECTION FOR CELLS C_{10}, C_{18} AND C_{33}.

c_t	d_1	d_2	d_3	d_4	d_5	d_6	
10	4	4	2	3	3	3	$\|\|RD_{dj}\|\|_{10}$
18	2	1	3	0	1	2	$\|\|RD_{dj}\|\|_{18}$
33	1	2	1	1	3	2	$\|\|RD_{dj}\|\|_{33}$

TABLE II. THE NUMBER OF COMPRESSED ROADS SET FOR THE CONSIDERED CELLS.

c_t	cf_t=0,2	cf_t=0,4	cf_t=0,6	cf_t=0,8	
10	{4,4,2,2,2,2}	{2,2,2,2,2,2}	{2,2,1,2,2,2}	{1,1,1,1,1,1}	$\boldsymbol{\Lambda_{10}}$
18	{2,1,2,0,1,2}	{2,1,2,0,1,2}	{1,1,2,0,1,1}	{1,1,1,0,1,1}	$\boldsymbol{\Lambda_{18}}$
33	{1,2,1,1,2,2}	{1,2,1,1,2,2}	{1,1,1,1,2,1}	{1,1,1,1,1,1}	$\boldsymbol{\Lambda_{33}}$

First of all, a training campaign was performed in order to obtain the elements of DMC^t and ST^t, in function of the considered map, with c=42. The Kraub mobility model has been considered [7] (with Acceleration = 1.4m/s^2, Deceleration 2m/s^2, si=0.5 and τ=0.2s) for 1000 simulations with 2000s of duration and 270 vehicles for each run (low dense roads have been considered for this simulation campaign). Mobility log files have been obtained and, then, the coverage set of cells has been considered. Different compression factor cf^t values have been used, as well as different coverage radius values R. We assume that each cell is able to recognize the possible roads with DoA or Angle-of-Arrival (AoA) approaches.

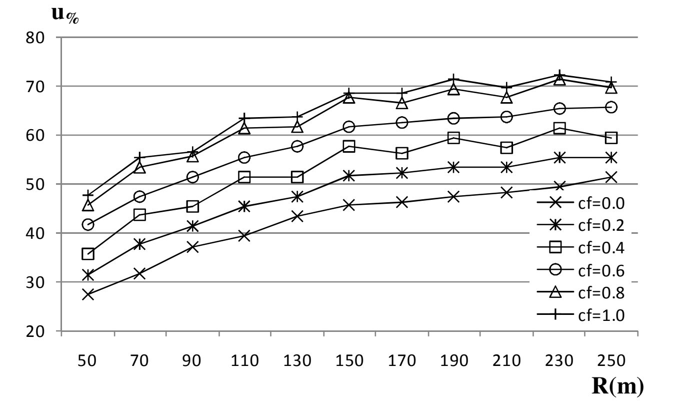

Fig. 10. Average system utilization for different values of R and compression factor cf.

Fig. 10 shows how the system responds to DMPA in terms of system utilization, calculated as the average of the ratio between the active bandwidth slots and the total ones, for each cell. It is evident how, in general, the system is under-utilized ($u_{\%}$ belongs to the range [25, 75]). There is an increasing trend for higher coverage radius: when the number of cells decreases from 42 to 10 (as illustrated in fig. 7), there is a lower number of passive reservations (lower cells have to be predicted because of the higher geographical covered region). In this case, also the protocol overhead decreases, because there is a lower number of cells among which the signaling packets have to be exchanged

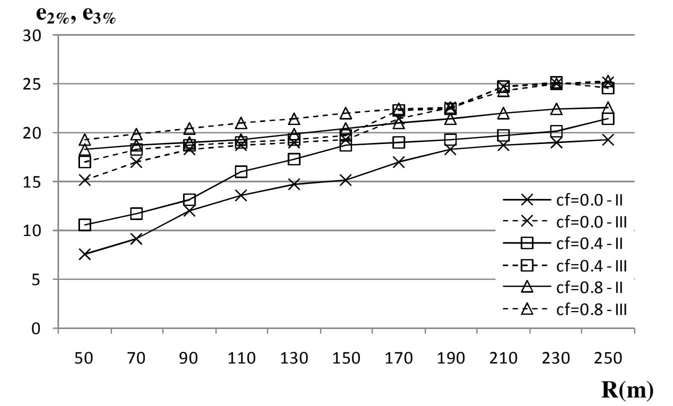

Fig. 11. Average prediction error for 2nd and 3rd hand-over events with different values of R and compression factor cf.

. For the same reasons, $u_{\%}$ increases when the algorithm employs a higher grade of roads compression: when $cf \rightarrow 1$, the number of partition sets for each side $\|RD_{dj}\| \rightarrow 1$, so only one possible direction needs to be considered for each side and the overhead is reduced. Figure 11 gives a description of the trend of the prediction error for the second ($e_{2\%}$) and third ($e_{3\%}$) hand-over events, given that $e_{1\%}$=0. For a single simulation, it is evaluated as the ratio among the number of users that do not find a passive reservation after the hand-over event and the number of total 2nd or 3rd hand-over events during simulation time. The trend is increasing both for higher coverage radius (host movements are more casual if the considered area is larger) and cf values (system looses the granularity about users movements). The maximum obtained value is 25.3%. In Fig. 12 the course of the CBP is illustrated. It is evident how for larger R it decreases, because each cell will cover a larger geographical area (so it will serve more users), while the number of available slots remains the same. In addition, for higher cf values, there is a slight decreasing of CBP because, for higher prediction values, the system overestimates the available resources and admits more users.

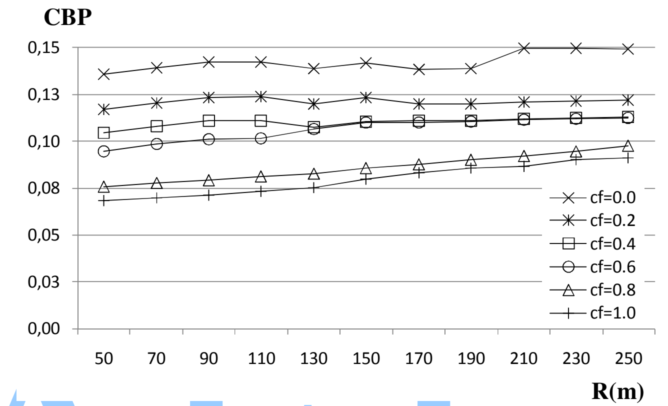

Fig. 12. Trend of CBP vs R and cf.

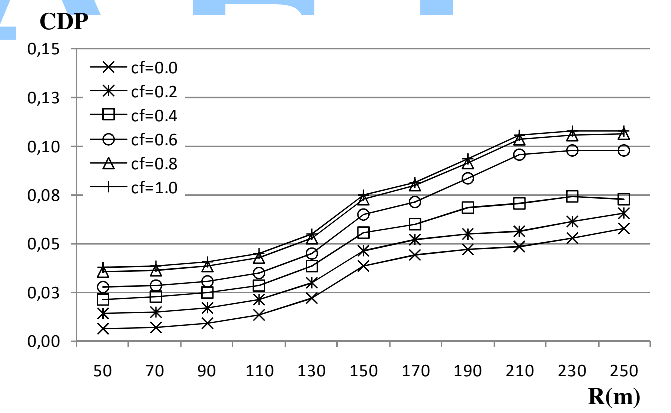

Fig. 13. Trend of CDP vs R and cf.

Figure 13 shows the trend of the CDP for different values of R and cf. For small coverage areas there is a negligible probability of call dropping (below 5%) because of (based also on the trend of prediction error) more deterministic host movements in the network. In addition, a higher value of cf brings the prediction algorithm to lose more roads information granularity, arriving to the simplest case of one direction for each coverage side.

V. CONCLUSIONS

This work proposes a new Markovian prediction model, DMPA, optimized in terms of number of states. The dynamic programming approach is employed to compute an adequate number of states, able to reflect roads topology properties and mobile hosts behavior. It is also able to guarantee service continuity in QoS networks, without disrupting system utilization performance. The main strength of DMPA resides in the integration of the Markov predictor and the time roads compression scheme, leading to very good performance in terms of prediction error, utilization, CBP and CDP. After many considerations regarding DMPA performance, we highlighted that that a compression factor of 0.4 can be enough to reduce the number of computations of the Markov model, ensuring a good trade-off in performance results.

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