Dynamic Advertising in VANETs using Repeated Auctions

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Abstract—Vehicular ad-hoc networks (VANETs) have been an active area in the research community during the last decade with focus primarily on routing protocols, security aspects and safety. Recent advances in wireless communication and the inherent dynamic nature of VANETs provide excellent opportunity for advertisement dissemination. In this paper, we address the problem of dynamic advertising in VANETs. We consider a city divided into a grid, where the blocks have different vehicular densities that vary over time. Several advertising companies compete for the blocks to broadcast their advertisements in the network. The content dissemination in the network is controlled by a data management unit that receives requests from advertising companies for each block. To solve the problem of block allocation, we adopt the repeated auction scheme for the dynamic setting. Two new metrics are defined to better represent the real-world scenario and fairness in repeated auctions. We propose an algorithm which is a combination of adaptive linear prediction and nonparametric Bayesian belief update, enabling smart bidding and improving the utilities of the competing advertising companies significantly in the long-run. Through simulations, we show that the proposed algorithm achieves better performance than two baselines approaches.

Keywords—Vehicular ad-hoc networks, repeated auctions, advertising, Dirichlet process, nonparametric Bayesian learning, adaptive linear prediction.

I. INTRODUCTION

Vehicular ad-hoc network is an active research area due to its promising potential in improving road safety and transportation efficiency [1]. Most of the research in VANETs has been focused on routing protocols, broadcasting algorithms and security [2], [3]. Moreover, there are ample open challenges in the area of VANETs that need to be resolved, ranging from standardization, development and deployment.

An important factor which can boost applications of VANETs is the advent of autonomous cars by around 2020. Henceforth, people would be able to perform other tasks, like checking emails, reading news, watch videos, etc., in the vehicle. Also, the mobility and increased connectivity enable several new opportunities such as multimedia streaming, and vehicular social networking [4].

During drive-times the target rate of audio advertisements in AM/FM radio stations is very high [5]. The advent of autonomous driving and multimedia broadcasting in VANETs provide a great opportunity for the commercial companies to capitalize on this segment to advertise their products and services.

In this paper, it is assumed that a city is divided into a grid of blocks with different densities of vehicles varying dynamically over time, and there is a data management unit which manages content dissemination in the network. Several advertising companies compete for accessing the blocks to broadcast their advertisements. The data management unit conducts repeated auctions to rent out the VANET infrastructure in each block to the advertising companies. The advertising companies act as bidders, who bid repeatedly in successive time-slots for the blocks depending on their valuations.

A. Related Work

The mobile advertising problem in vehicular networks is discussed in [6]. The core idea of this paper is to leverage the contact behavior of the network in future to improve mobile advertising. In particular, the authors have proposed Markov chains and a greedy heuristic to capture the dynamics of the vehicular network and eventually determine a set of seed vehicles for advertisement dissemination. However, it does not consider the scenario where multiple advertising companies compete for broadcasting their advertisement. In our work, we consider auctions to rent the VANET infrastructure for competing entities. Several works related to auction can be found in the context of spectrum sharing in cognitive radio networks [7], [8], [9]. In [7], two-stage group buying spectrum auction schemes are proposed with an objective to increase the purchasing power of the small service providers in a cognitive radio network. Single-price and VCG-like auctions are conducted between SUs-SAPs and SAPs-PUs, respectively with a focus on the static network. In [8], optimal bidding in repeated auctions is discussed for the spectrum access problem, and a distributed learning based bidding algorithm is proposed. The primary emphasis of this paper is on optimal bidding with budget constraints. However, in our paper, we focus on repeated auctions and judicious bidding with the help of learning and prediction methods in a general dynamic setting.

B. Contributions

In this paper, we attempt to solve the problem of dynamic advertisement in VANETs by using repeated auctions. We adapt the idea of repeated auctions and nonparametric Bayesian learning from [9] with necessary enhancements to the dynamic scenario. We augment the scheme by using adaptive linear prediction in conjunction with the Dirichlet process (DP) based nonparametric Bayesian learning and verify the

1VCG - Vickrey-Clarke-Groves, SU - Secondary Users, PU - Primary Users, SAP - Secondary Access Point.
performance improvement through simulations. We define new metrics with respect to repeated auctions, which reflect the bidders’ behavior and ensures fairness to both the bidders and the auctioneer. To the best of our knowledge, it is one of the first works in this area that considers the interaction between advertising companies and the data management unit for the purpose of dynamic advertising in VANETs. Moreover, through simulations we show that the method of repeated auctions augmented with DP based learning and adaptive linear prediction shows significant improvement in performance compared to the DP based learning alone.

C. Structure of the paper

The remainder of the paper is structured as follows: the system model is introduced in section II. The repeated auction mechanism is explained in section III. The concept of Nonparametric Bayesian learning is discussed in section IV. Adaptive linear prediction and belief update post prediction are described in section V. The simulation results are presented in section VI. Finally, we conclude the paper in section VII.

II. SYSTEM MODEL

We consider a city to be divided into a grid of blocks with different vehicular densities. Due to the movement of vehicles, these blocks have different vehicular densities that evolve over time. Each block has one or more roadside units (RSUs) that broadcast data to vehicles. These RSUs can be small cell eNodeBs, WiFi hotspots or simply macro base stations, which are connected to data management unit through the network backbone. Several advertising companies communicate with the data management unit to rent the VANET infrastructure for broadcasting advertisements. One of the possible approaches to resolve the demands of competing entities is by conducting auctions at every time-slot.

The advertising companies act as bidders, who compete for the blocks. The valuations of the bidders for each block are assumed to be proportional to the densities of vehicles inside the block. Larger block density (e.g. In the downtown area) implies that the broadcasted content is visible to a larger number of people. However, the bidders may have different valuations based on their individual preferences (for instance, demographic priorities, target rate history, etc). The data management unit acts as an auctioneer. Prior to bidding, the data management unit notifies the base price for the bidders. Moreover, the block densities exhibit temporal correlation which enables the bidders to both learn from the auction history and predict the future trends. Thus, the three aspects, namely the base price, learning from the history of auctions and predicting the future prices enable the advertising companies to bid in a smart manner. The data management unit evaluates the bids and announces the winner and the payment. Fig. 1 shows a top level diagram of the scenario considered in this paper.

Fig. 1. Top level diagram depicting the bidders interacting with the data management unit and the advertisement broadcasting in a VANET.

III. REPEATED AUCTION MECHANISM

As described in the previous sections, we consider repeated second-price auctions to resolve the demands of competing commercial companies for the purpose of broadcasting advertisements in the network. One advantage of second-price auction is that it admits truthful bidding as a dominant strategy
reward with a decay factor $\tau_d(d_k^{n,t})$, which is a function of the normalized block density $d_k^{n,t} = d_k^n/d_{\text{max}}$ and is defined as $\tau_d(d_k^{n,t}) \triangleq d_k^{n,t}\tau_{min} + (1 - d_k^{n,t})\tau_{max}$. On the other hand, if a bidder chooses to stay out of the auction for a certain duration, then the effective reward will be restored and he would enjoy the true instantaneous reward. We call the duration as recovery time, which is defined as $\tau_r(d_k^{n,t}) \triangleq d_k\tau_{min} + (1 - d_k^{n,t})\tau_{max}$. The decay factor and recovery time are bounded in $[\tau_{d_{min}}, \tau_{d_{max}}]$ and $[\tau_{r_{min}}, \tau_{r_{max}}]$, respectively and their values depend on the instantaneous block density. The underlying rationale is that if a block is well-populated, the effect of the advertisement due to repeated broadcast decreases very slowly with time. On the contrary, after a session of repeated advertisements, if the block density is high, then the advertising company is required to wait only for a short duration of time until the effectiveness is restored to the maximum value. In this respect, the time elapsed since the bidder $i$ won the last bid for block $k$ until time $t - 1$ is given by

$$\tau_{e_{i,k}} := (1 - \gamma_{t_i,k}^{-1})\tau_{e_{i,k}}^{-1} + 1.$$ \hspace{1cm} (5)

When the elapsed time equals or exceeds the recovery time, the advertisement will attain the same effectiveness as it were disseminated at time $t = 0$ with the same block density. In this paper, we assume that recovery of advertising effectiveness is linear with time. The rate of recovery is given by

$$\kappa_{i,k}^t = (1 - w_{i,k}^{t-1})/\max\left(\tau_r(d_k^{n,t}) - \tau_{e_{i,k}}^{-1}, 1\right).$$ \hspace{1cm} (6)

Now, we are ready to define the so-called reward scaling factor that models the variation in the effectiveness of advertisement with respect to time.

**Definition 1.** The reward scaling factor is defined as

$$w_{i,k}^t \triangleq \left(1 - (1 - \exp(-1/\tau_d(d_k^{n,t})))\gamma_{i,k}^{-1}\right)w_{i,k}^{t-1} + (1 - \gamma_{i,k}^{-1})\kappa_{i,k}^t.$$ \hspace{1cm} (7)

where $\tau_d(.)$ is the decay time, $d_k^{n,t}$ is the normalized block density of block $k$ at time $t$, $\gamma_{i,k} \in \{0, 1\}$ is the auction result corresponding to bidder $i$ in the previous time-slot.\(^4\) The scaled valuation at time $t$ is defined as

$$v_{i,k}^t \triangleq w_{i,k}^t\theta_{i,k}^t.$$ \hspace{1cm} (8)

where $\theta_{i,k}^t$ is the original valuation, i.e., the bid value without rescaling depending on the auction history. The objective of each user is to maximize the overall payoff by participating in or staying out of the auction. Mathematically, the maximum payoff of each user is given by [9]

$$u_{i,k}^{t,\text{max}} = \max_{b_i \in \{0, v_{i,k}^t\}} E\{v_{i,k}^t\}.$$ \hspace{1cm} (9)

where $v_{i,k}^t = \sum u_{i,k}^t$ is the utility of bidder $i$ at time $t$. It can be noted that, solving the Eq. 9 is NP hard. Hence, we decide suboptimally that for each block a bid can be placed if the expected utility is greater than that of staying out (SO), i.e., $u_{i,k}^t(b_{i,k}^t = 0) < E v_{i,k}^t(b_{i,k}^t = u_{i,k}^t)$. This suboptimal decision results in linear complexity.

**Utility Computation:**

To estimate the expected utility of bidder $i$, the knowledge of the distribution of other bidders’ bids is required. Since, the bidders do not communicate with each other, we need to estimate the distribution from the bidding history. In particular, the cumulative distribution function (CDF) is given by, $F_k(v_{i,k}^t) = \textbf{P}(\max(b_{i,k}^t < v_{i,k}^t)$ represents the bidder $i$'s belief about winning block $k$ at time $t$ using the bid value $v_{i,k}^t$, which is obtained by sampling the Dirichlet distribution to be discussed in Eq. (23). The accumulated cost of bidder $i$, for block $k$ at time $t$ is given by

$$c_i^{t-1}(h_{i,k}^{t-1}) = \sum_{j=1}^t \beta^{t-j} \left(p_{i,k}^j \gamma_{i,k}^j + c_{\text{bid}} 1(b_{i,k}^j \neq 0) + e_{i,j}^t\right),$$ \hspace{1cm} (10)

where $h_{i,k}^{t-1}$ is the auction history observed by the bidder $i$ till time $t - 1$, $\beta$ is the factor which signifies the degree of history retention and $p_{i,k}^j$ is the payment, $c_{\text{bid}}$ is the bidding cost, $e_{i,j}^t$ is the entry fee and $\gamma_{i,k}^j$ is the block allocation vector at time $t_j \leq t$. Similarly, the accumulated reward is given by

$$r_{i,k}^{t-1}(h_{i,k}^{t-1}) = \sum_{j=1}^t \beta^{t-j}v_{i,k}^j \gamma_{i,k}^j.$$ \hspace{1cm} (11)

If the bidder wins the auction for the block $k$ at time $t$, then the utility is given by

$$u_{i,k}^{t,\text{w}} = (r_{i,k}^{t-1}(h_{i,k}^{t-1}) + u_{i,k}^{t+1} - u_{i,k}^{t+1}) - (c_{i,k}^{t-1}(h_{i,k}^{t-1}) + c_{\text{bid}} + e_{i,k}^{t-1} + p_{i,k}^t).$$ \hspace{1cm} (12)

where $u_{i,k}^{t+1}$ is the minimum utility every user gets just by registering for an auction (e.g. data about real-time pricing), $c_{\text{bid}}$ is the bidding cost and $e_{i,k}^t$ is the entry fee at time $t$. On the other hand, if the bidder loses the auction, then the utility is given by

$$u_{i,k}^{t,l} = (r_{i,k}^{t-1}(h_{i,k}^{t-1}) + u_{i,k}^{t+1}) - (c_{i,k}^{t-1}(h_{i,k}^{t-1}) + c_{\text{bid}} + e_{i,k}^{t-1} + p_{i,k}^t).$$ \hspace{1cm} (13)

Then the estimated expected utility can be written as

$$\hat{E}v_{i,k}^t(u_{i,k}^t) = u_{i,k}^{t,l}(1 - F_k(v_{i,k}^t)) + u_{i,k}^{t,w} F_k(v_{i,k}^t),$$ \hspace{1cm} (14)

where $u_{i,k}^{t,w}$ and $u_{i,k}^{t,l}$ represent the utility when the bidder wins and loses the auction, respectively.

Consider a case in which at least two bidders have their valuations greater than the base price and fewer than two bidders participate in the auction. Such instances would adversely affect the auctioneer’s revenue. To encourage the bidders not to stay out of the auction, the auctioneer charges the boycotted bidders with no-show penalty, when less than two bidders participate in the auctions, which is defined as

$$q_{i,\text{min}}^t \triangleq \lambda p_{i,\text{min}}^t, i : b_{i}^t = 0 \text{ and } \sum_{t=1}^N 1(b_{i,k}^t) \in \{0, 1\}$$ \hspace{1cm} (15)

where the constant $\lambda > 0$ and $p_{i,\text{min}}^t$ is the base price. Since, the bidders are selfish and do not cooperate, when
the expected utility is lower than that of staying out, the selfish bidders prefer to stay out of the auction unilaterally without considering social welfare. Hence, no-show penalty is not considered while making the bidding decision by any bidder/s.

IV. NONPARAMETRIC BAYESIAN LEARNING

To learn the distribution of competing bidders we consider nonparametric Bayesian learning, where we improve the estimated expected utility by obtaining more observations. In general, Dirichlet process is commonly used for nonparametric Bayesian learning, since it provides a simple and elegant way of belief update. First, a brief review of Dirichlet process is provided. Then, we discuss how it is adapted to the VANET advertisement problem. Also, we omit the subscripts $i$ and $k$ in this section, since the belief update procedure is the same for all blocks and bidders.

Definition 2. The Dirichlet distribution is defined as

$$\text{Dir}(\alpha_1, \ldots, \alpha_M) = \frac{\prod_{i=1}^{M} \Gamma(\alpha_i)}{\Gamma(\sum_{i=1}^{M} \alpha_i)} \prod_{i=1}^{M} x_i^{\alpha_i - 1} ,$$

(16)

where the probability simplex $\sum_{i=1}^{M} x_i = 1$ is the support with $x_i \geq 0$, $\forall i \in [1, M]$ and $(\alpha_1, \ldots, \alpha_K)$ are the scaling parameters. Dirichlet distribution is the conjugate prior of the multinomial distribution [12]. This property enables us to update our beliefs just by updating the parameters of the Dirichlet distribution based on the observations.

Dirichlet Process:

Dirichlet process is a stochastic process whose realizations are probability distributions, which is defined below.

Definition 3. The Dirichlet process is defined as

$$(G(X_1) \ldots (G(X_M))) \sim \text{Dir}(\omega G_0(X_1), \ldots, \omega G_0(X_M)),$$

(17)

and is denoted by $G \sim \text{DP}(\omega, G_0)$, where $X$ denotes the measurable space, $G_0$ is the base measure on $X$ and $\omega$ is the concentration parameter. The random distribution $G$ on $X$ is said to be drawn from a Dirichlet process if its measure on any finite partition follows a Dirichlet distribution.

Posterior Belief Update:

If $x^1, \ldots, x^t$ is the sequence of observations and $n_m$ is the number of observations in partition $X_m$, then the posterior distribution can be written as

$$(G(X_1) \ldots (G(X_M))) | x^1, \ldots, x^t \sim \text{Dir}(\omega G_0(X_1) + n_1, \ldots, \omega G_0(X_M) + n_M).$$

(18)

We quantize the payment into $M$ discrete quantities forming a partition $X_1, \ldots, X_M$. If $p^t_{\text{min}}$ is the minimum payment set by the auctioneer, then we consider the prior distribution to be a point mass, $\omega G_0(X_m) = \delta(p^t_{\text{min}} \in X_m)$. We consider this prior because the bidders are certain that none of his competitors with $v^t < p^t_{\text{min}}$ will participate in the auction at time $t$. If $p^t_1, \ldots, p^t_t$ is the sequence of payments observed by the bidder (announced by the auctioneer), then the number of payments that belong to the partition $X_m$ is given by

$$n_m = \sum_{i=1}^{t} \zeta^{-1} \cdot 1(p^t \in X_m),$$

(19)

where $\zeta = 1 - \zeta$ is the payment forgetting factor and $m \in [1, M]$. When the block densities vary with time, the auction history beyond a certain duration is not useful because it does not reflect the present situation. Therefore, the forgetting factor is introduced to adapt to the dynamic environment. If $p^t_{\text{min}}, \ldots, p^t_{\text{min}}$ is the sequence of base prices set by the auctioneer, then the posterior Dirichlet process is given by

$$G | p^t_1, \ldots, p^t_t, p^t_{\text{min}}, \ldots, p^t_{\text{min}} \sim \text{DP} \left( \omega + t, \frac{1}{\omega + t} \left( \omega G_0 + n_m \right) \right).$$

(20)

As explained in section III, by sampling Eq. 20, CDF of opponent’s can be obtained, which is used to make the bidding decision.

V. PREDICTION - ADAPTIVE LMS GRADIENT ALGORITHM

In section II, it was mentioned that since the block densities vary in a correlated manner, prediction can potentially improve the average utility of the bidders. This is due to the fact that by predicting the current payment from the past observations, the contenders can make better bidding decisions. In this section, we describe linear prediction using the least mean square gradient algorithm [13] to predict the payment $p^t_{\text{min}}$ and the base price $p^t_{\text{min}}$ for the succeeding time-slot. The predicted payment is given by

$$\hat{p}^{t+1} = \sum_{i=1}^{L} a^t_i p^{t-i},$$

(21)

where $a^t_i$’s are the coefficients of the adaptive linear predictor and $L$ is the order of the filter. The coefficient update is performed as

$$a^{t+1}_i = a^t_i + \mu \left( p^t_i - \sum_{j=1}^{p} a^t_j p^{t-j} \right),$$

(22)

where $i = 1, \ldots, L$ and $\mu$ determines the rate of adaptation. The base price $p^t_{\text{min}}$ is predicted in the same manner.

Belief-Update Post Prediction:

From prediction, we obtain information about the future, which can further improve the existing belief that is merely based on history. If $\hat{p}^{t+1}$ is the predicted payment and $p^t_{\text{min}}$ is the predicted base price, then the posterior DP can be further updated as

$$(G(X_1) \ldots (G(X_M))) | p^1, \ldots, p^t, \hat{p}^{t+1}, p^t_{\text{min}}, \ldots, p^t_{\text{min}}, p^t_{\text{min}} \sim \text{Dir}(\omega G_0(X_1) + \zeta n + \delta(\hat{p}^{t+1} \in X_1),$$

\ldots, \omega G_0(X_M) + \zeta n + \delta(\hat{p}^{t+1} \in X_M)).$$

(23)

Algorithm 1 summarizes the mechanism of repeated auctions with DP based learning and adaptive linear prediction. The steps 1 through 7 constitute the algorithm for DP based learning without the prediction stage.

VI. SIMULATIONS

In our simulations, we consider the geographical area of the city which is divided into a grid of size 20x20. Each block contains different densities of vehicles distributed uniformly in the range $[d_{\text{min}}, d_{\text{max}}]$. We have assumed $d_{\text{min}}$ and $d_{\text{max}}$ to be 200 and 2000 respectively. The evolution of block densities...
is modeled as a correlated Gaussian random process. The temporal correlation is generated by filtering the uncorrelated Gaussian process ($g^t_k$) using a low pass filter ($h^t$) with passband and stopband cut-off frequencies (normalized) chosen as 1/6 and 1/4, respectively, and the filter order $N_{fil} = 177$ ($g^{t,corr}_k = h^t \ast g^t_k$). Then, the block density is obtained as $d^t_k = d_{min} + g^{t,corr}_k(d_{max} - d_{min})/\max\{g^{t,corr}_k\}$. This is an ideal model and might not model the real dynamics accurately, but the nature of our results remain the same irrespective of the model of dynamics. Different commercial companies have distinct individual distributions distributed uniformly with the range $[v^t_\mu - 100, v^t_\mu + 100]$ and the instantaneous block density as the mean ($v^t_\mu \approx d^t_k$). We assume that the relative differences in the valuations remain constant with respect to time. We consider 100 bidders, both the entry fee ($c^t$) and the bidding cost ($c^t_{bid}$) are considered to be 20 and no show penalty is set to be 2 percent of the base price $p^t_{k, min}$. We consider $p^t_{k, min}$ to be equal to the instantaneous block density, $d^t_k$. The concentration parameter is set as $\omega = 1$. The order of the adaptive linear predictor $P = 40$ and the rate of adaptation $\mu = 2 \times 10^{-8}$. In the simulations we compare the performance in both static and dynamic environments for the three schemes viz. 1) Naïve bidding, where all the bidders bid for every time-slot. 2) DP scheme and 3) DP-LP (DP scheme with linear prediction). We compare the average (and cumulative) costs and utilities of the above schemes. However, in contrast to section III, we consider instantaneous utility, which does not include history. Similarly, the average cost and the average reward considered for evaluation are given by $c^t_{avg} = \frac{1}{K N} \sum_i \sum_k p^t_{i, k} v^t_{i, k} + c^t_{bid} \mathbb{I}(b^t_{i, k} \neq 0) + c^t$ and $r^t_{avg} = \frac{1}{K N} \sum_i \sum_k v^t_{i, k} e^t_{i, k}$, respectively.

1) Static Environment: First, we simulate the proposed algorithm for static block densities. In the static case, $\beta$ and $\zeta$ are set to 0.6 and 0.4, respectively, for adequate utilization of history for learning. From Fig. 2, we can observe that average utility of DP increases rapidly due to belief update and converges subsequently. From Fig. 3, it can be observed that the reward of DP is almost equal to or slightly lower than naive bidding. This small deviation is because of some randomness introduced due to the sampling of Dirichlet distribution. Despite this, DP performs significantly better than naïve bidding (by about 82%) because of low average cost achieved by potential losers staying out of the auction. However, adding linear prediction does not help in improving the performance beyond that of DP alone. This is expected since the block densities are static. Also, there is a marginal degradation (about 2.16%) in utility relative to DP because of small prediction errors.

2) Dynamic Environment: Fig. 4, 5 depict the simulation results for the case when block densities vary rapidly, but in a correlated fashion. This variation can occur in situations when the successive auctions have several minutes of time gap in between them (for instance, advertisements broadcasted between successive overs in a cricket match or in any multimedia streaming). We compare the performance of the same three schemes mentioned above. Here the factors $\beta$ and $\zeta$ are set to 0 and 0.8, respectively, thereby giving no/less weight to history. The subplots in Fig. 4 depict the average cumulative utilities of naïve, DP and DP-LP methods and percentage improvement of DP-LP method relative to DP and naive bidding schemes. It can be seen that the average cumulative utility for DP-LP is the highest, followed by DP and finally naïve bidding. However, it turns out that naïve bidding has the highest reward since all the bidders participate in the auction at every time-slot. On the other hand, DP has the lowest reward because only the knowledge of history is considered in the method. Since the block densities vary rapidly, even the quantities corresponding to the previous time-slot do not represent the present scenario well. Due to the poor performance of DP and given the
try to access these blocks through the data management unit that rents out the network infrastructure to broadcast their advertisements. We adopt the method of repeated auctions for solving the problem of block allocation for advertisement spreading in the network. Repeated auctions are conducted by the data management unit as the auctioneer and commercial companies as bidders. We define two new metrics in the context of repeated auctions that mimic the real-world scenario in VANETs, namely reward scaling factor and no-show penalty. For smart bidding in the time-evolving network, we propose an algorithm, which is a fusion of nonparametric Bayesian learning and adaptive linear prediction. Smart bidding enables the commercial companies to achieve the objective of targeting large number of vehicles with judicious investment. Simulations demonstrate that the proposed combined scheme achieves higher average utility than nonparametric Bayesian learning and naive bidding schemes in the dynamic setting.

In this paper, the vehicular dynamics is modeled as correlated Gaussian random process. Instead, realistic mobility models could be considered. It would be interesting to evaluate the performance of the algorithm under budget constraints. It would also be worthwhile to compare the proposed algorithm with other bidding methods than naive bidding scheme alone.

VII. CONCLUSION

In this paper, we addressed the problem of dynamic advertising in VANETs in the presence of multiple contenders. The geographical area of a city is considered to be divided into a grid of blocks with time varying vehicular densities inside these blocks. Each block has one or more roadside units which communicate with the vehicles. The commercial companies

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