On-road Ads Delivery Scheduling and Bandwidth Allocation in Vehicular CPS

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Abstract-**We consider a promising application in Vehicular Cyber-Physical Systems (*VCPS*) called *On-road Ad Delivery* (*OAD*), where targeted advertisements are delivered via roadside APs to attract commuters to nearby shops. Different from most existing works on VANETs which only focused on a single technical area, this work on OAD involves technical elements from human factors, cyber systems and transportation systems since a commuter's shopping decision depends on e.g. the attractiveness of the ads, the induced detour, and traffic conditions on different routes. In this paper, we address a new optimization problem in OAD whose goal is to schedule ad messages and allocate a limited amount of AP bandwidth so as to maximize the system-wide performance in terms of *total realized utilities* (*TRU*) of the delivered ads. A number of efficient heuristics are proposed to deal with ad message scheduling and AP bandwidth allocation. Besides large-scale simulations, we also present a case study in a more realistic scenario utilizing real traces collected from taxis in the city of Shanghai. In addition, we use a commercial traffic simulator (PARAMICS) to show that our proposed solutions are also useful for traffic management in terms of balancing vehicular traffic and alleviating congestion.**

Keywords-On-road Ad Delivery; Human-in-the-Loop; Daily Commuters; Shopping Activities; Vehicular CPS;

I. INTRODUCTION

Vehicular Cyber-Physical System (*VCPS*) aims to integrate computing/communication capabilities with transportation systems for supporting various applications, e.g., road safety improvement and on-road infotainment, etc. This work is motivated by the observation that the following three essential aspects are still missing from most of the existing works:

Firstly, prior research in VANET has paid much attention to the design of optimal protocols for a given scenario in the physical world [18-21] but little on the interaction, e.g., mobility modeling looks into how node mobility can affect the performance of protocols in the cyber systems. However, how the information delivered by these protocols can in-turn affect the node behavior has not been examined adequately.

Secondly, the human element, who is still an irreplaceable element in both cyber and transportation systems, has largely been ignored when designing network protocols. However, most of the information delivered terminates at the human-end, and in particular, vehicle mobility largely depends on the human driving behavior. Traditional research [2-5] on human
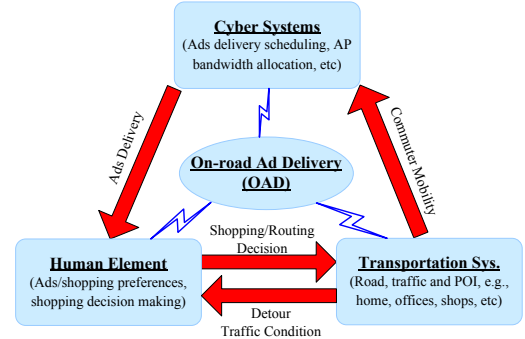

Fig. 1. The general concept of On-road Ad Delivery (OAD)

factors has mainly focused on how human could be affected by external factors such as road signs, on-board systems, or other environmental aspects. Nevertheless, how to design effective protocols in the cyber systems to proactively affect human behaviors is still largely unexplored [1].

Thirdly, although today's e-displays for road-side ads are used by some merchants, the effectiveness of this approach is not clear because of its inability to cater to individual's shopping preferences. By comparison, online targeted advertising [8] can deliver ads to attract customers based on their search/email contents, web browsing, etc, but it mainly targets people at home rather than on the road. Additionally, very little is known about how such targeted ads may affect people's online behaviors, let alone how targeted ads delivered to commuters may affect their traveling routes and activities.

Overall, the novelty of this work comes from three aspects: 1) we address a new optimization problem called *On-road Ad Delivery* (*OAD*), which aims to deliver targeted ads to commuters; 2) we consider human to be an essential element in VCPS and include human shopping decision modeling in our OAD problem; 3) we address the interactions between the human, the cyber and the transportation elements.

A typical scenario for OAD is as follows. Imagine that everyday, most commuters plan to go home directly after work. During their trip home, they receive various targeted ads (e.g., video-based) from different shops that are delivered through road-side APs by an ad delivery agency. On one hand, each ad can bring a *potential utility* to a shop (in terms of revenue, profit or reduced shelf space, etc). On the other hand, depending on individual's preference or shopping interest, the same ad can have different attractiveness to different people. Accordingly, the potential utility of an ad (ad_1) from shop (sp_1) can be *realized* from commuter u_A only if u_A has received ad_1 and decides to visit sp_1. Note that, several factors may affect her decision about whether to visit a shop, including the

attractiveness of the received ads, the induced detour and the traffic conditions of the original route and the detour.

Within the context of the above application, we address the following *OAD Problem*: Given the limited wireless resources (e.g., limited AP bandwidth/coverage), a number of ads from different shops to be delivered, and the known shopping preferences of the commuters, how to deal with ad delivery scheduling and AP bandwidth allocation so that the system-wide performances in terms of *total realized utilities* (*TRU*) of the delivered ads can be maximized. OAD reflects the interactions and feedback loop between three technical areas, as shown in Fig.1. For example, the delivered ads may affect commuters' shopping decisions, and then if commuters decide to go shopping (thereby taking a detour), it subsequently leads to different AP bandwidth allocation and ad delivery results along a given route. Likewise, route changes have influence on traffic conditions, which in turn is a factor considered by commuters when making their shopping decisions.

The main contributions of this work are as follows:

• To the best of our knowledge, no existing work has addressed the feedback loop between human elements, cyber systems and transportation systems. In particular, this work is the first that studies such an on-road ad delivery application.

• Different from existing online advertising paradigms, we introduce a realistic shopping decision model based on the unique characteristics of OAD, whose goal is to maximize the realized utilities of the delivered ads, instead of maximizing data throughput (a focus of the most of existing works).

• We propose a list of solutions based on different considerations to address the challenges related to ad delivery scheduling and AP bandwidth allocation.

• We analyze the performances of the proposed solutions using large-scale simulations. In particular, we present a case study of an area in Shanghai by using real taxi traces.

• We utilize a commercial traffic simulator PARAMICS to demonstrate that our solution is useful for traffic management in terms of balancing road traffic and alleviating congestion.

The paper is organized as follows. In Sec. II, we present assumptions, models and definitions. The detailed solution design is presented in Sec. III, followed by the performance evaluation in Sec. IV. We present a case study in Sec. V and conduct traffic-related evaluation in Sec. VI. We discuss the related work in Sec. VII, and Sec. VIII concludes the paper.

II. PROBLEM DESCRIPTION

A. Basic Scenario

We study OAD in a given period, say $t \in [0, T]$ (e.g. evening peaking hours). During this period, there are n commuters (denoted by $\{u_i\}$, $i=1,2,\ldots n$) and each of them is associated with a vehicle and will start a trip from her source src_i towards destination dst_i, which typically are the workplace and the home of u_i, respectively. Each vehicle has the capability to communicate with the scattered road-side APs (denoted by $\{AP_k\}$, $k=1, 2,\ldots p$) and each of APs has a total bandwidth tbw_k and a coverage range cr_k.

There are m shops (denoted by $\{sp_j\}$, $j=1,2,\ldots m$) distributed in the road network. For each shop sp_j, it has a number of ads to be delivered (we assume that most of them are mainly in rich multimedia format and hence consumes a non-negligible
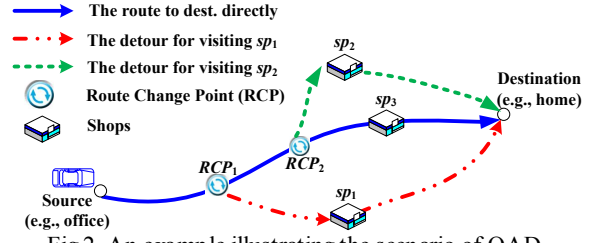

Fig 2. An example illustrating the scenario of OAD

amount of AP bandwidth). We denote the hth ad from shop sp_j by $ad_{j,h}$ with the data size $size_{j,h}$ and the set of ads from sp_j are denoted by $ads(j)=\{ad_{j,h}\}$.

For a given $ad_{j,h}$ from sp_j and a commuter u_i, we denote its *potential utility* to sp_j by $utl_{j,h}$ and its attractiveness to u_i by $att_{i,j,h}$, respectively. The utility to a shop could be the profit or other benefits e.g., shelf space saving. The attractiveness of an ad to a potential commuter depends on her shopping preferences and interest, and also the promoted prices of the related products in the ad; these can be analyzed and estimated based on consumers' historical shopping records [9] (This work does not address the privacy issue involved).

For easy presentation, we assume that the commuters initially plan to go home directly without making any shopping plans but can be attracted by ads and decide to visit shops. In particular, for a given commuter u_i and a received ad $ad_{j,h}$, the potential utility of $ad_{j,h}$ can be *realized* from u_i if and only if u_i decides to visit sp_j. Note that, we are not concerned with whether u_i eventually buys some products (advertised or not) from the shop. In other words, as long as u_i visits sp_j, we consider $ad_{j,h}$'s potential utility to be realized.

B. Trip Model—Transpotion Sytem Domain

Recent research revealed that human activities and routes show a high degree of regularity, e.g., travel regularly to some places using almost fixed routes [14][17]. Therefore, in this work, we assume that for each commuter u_i, the route from src_i to dst_i is known to us by analyzing the commuters' mobility profile. Likewise, in reality, commuters prefer to take a minimum detour when visiting a shop by choosing an appropriate intersection along their original routes to start the detour. We call such an intersection a *route change point* with respect to shop sp_j for u_i (denoted by $rcp_{i,j}$). For example, in Fig. 2, the blue route is a commuter's initial route from source to destination without any shopping activity. The green and red routes starting from RCP$_1$ and RCP$_2$ are the detours when the commuter decides to visit sp_1 and sp_2, respectively.

C. Shopping Decision Model—Human Behavior Domain

We use the prior research on marketing as a guideline for our work [8-12]. For example, a recent research [12] reported that shopping intention may not be a sole indicator of consumers' purchase behavior. In OAD, while the attractiveness of ads can stimulate commuters' shopping intention, the actual shopping decision process is complicated and depends on several typical aspects, including:

a) The ad's attractiveness. The attractiveness of the received ads has a positive/important effect on commuters' shopping decisions. Since commuters will change routes at RCPs, we assume that u_i makes a decision to visit sp_j at $rcp_{i,j}$, based only on those ads that were received before arriving at

$rcp_{i,j}$. We define $bef_{i,j,h}$ as a Boolean function such that $bef_{i,j,h}=1$ means $ad_{j,h}$ has been received by u_i before $rcp_{i,j}$; and 0 otherwise. We denote the total attractiveness of the ads from sp_j received before $rcp_{i,j}$ by $TA_{i,j}$, which is given by:

$$TA_{i,j} = \sum_{ad_{j,h} \in ads(j)} att_{i,j,h} \times bef_{i,j,h} \tag{1}$$

b) The induced detour. The additional detour for visiting a shop has a negative effect on shopping decision. We denote the detour starting from $rcp_{i,j}$, via sp_j, to dst_i by $dt_{i,j}$ and the original route from $rcp_{i,j}$ to dst_i by $rt_{i,j}$. The lengths of $dt_{i,j}$ and $rt_{i,j}$ are denoted by $l\_dt_{i,j}$ and $l\_rt_{i,j}$, respectively. Normally, $l\_dt_{i,j} \geq l\_rt_{i,j}$ because commuters prefer to follow shortest paths, and $l\_dt_{i,j} = l\_rt_{i,j}$ is a special case in which sp_j is right along the original route (sp_3 in the example shown in Fig. 2). We define the *relative traveling length index* (or $TL_{i,j}$) as:

$$TL_{i,j} = \frac{l\_rt_{i,j}}{l\_dt_{i,j}} \tag{2}$$

Note that, $0 < TL_{i,j} \leq 1$. The larger it is, the shorter the detour to sp_j, and hence more incentive to a commuter for shopping.

c) Trip experience. Travel speed is always regarded as a popular indicator of trip experience. A consumer may intend to go shopping instead if $dt_{i,j}$ is less congested (and thus she can drive fast) than $rt_{i,j}$. We denote the average traveling speeds on $dt_{i,j}$ and $rt_{i,j}$ by $speed\_dt_{i,j}$ and $speed\_rt_{i,j}$, respectively and then we define the *relative trip experience index* (or $TE_{i,j}$) by

$$TE_{i,j} = \frac{speed\_dt_{i,j}}{speed\_rt_{i,j}} \tag{3}$$

A higher $TE_{i,j}$ has a similar effect in attracting a commuter to go shopping as having a higher $TA_{i,j}$ in the ads (or having a larger $TL_{i,j}$). To facilitate our formulation, we first normalize $TA_{i,j}$ and $TE_{i,j}$ to a 0-1 value as follows:

$$TA'_{i,j} = \frac{TA_{i,j}}{C}, \quad TE'_{i,j} = \frac{TE_{i,j}}{MTSR} \tag{4}$$

where C is a system-wide parameter indicating the maximum possible value of $TA_{i,j}$ (in our simulation, we set C as the total attractiveness of all the ads in the system), and $MTSR$ is the maximum traveling speed ratio between any two roads.

By considering all the above three factors, we then define the *Shopping Decision Index* (SD) of u_i for visiting sp_j:

$$SD_{i,j} = TA'_{i,j} \times TL_{i,j} \times TE'_{i,j} \tag{5}$$

where $0 < SD_{i,j} \leq 1$. Since making a shopping decision is complicated and a non-deterministic process, we use a probabilistic model by assuming that at intersection $rcp_{i,j}$, commuter u_i decides to visit sp_j with the probability:

$$P_{i,j} = \min\left(\frac{SD_{i,j}}{\Phi_{i,j}}, 1\right) \tag{6}$$

where $0 < \Phi_{i,j} \leq 1$ is a given empirical value, which corresponds to the degree of difficulty in attracting a commuter to a shop, hereafter called *resistance factor* (i.e., a smaller $\Phi_{i,j}$ means it is easier to attract a commuter). This value can be estimated based on commuters' historical shopping records (note that how to estimate $\Phi_{i,j}$ in reality is out of the scope of this work, and deserves a separated study).

Without loss of generality, we assume that each commuter will visit at most one shop during her trip, but this can also be easily extended (in fact, an entire shopping plaza can be modeled as a shop). In addition, once a commuter decides to visit a shop, she will not change her mind (e.g., not to shop, or to visit other shops along the way).

D. Wireless Network Model – Cyber Domain

We assume that there is a centralized ad-delivery agency connected to APs with high-speed connections. Therefore, Ads can be delivered by the agency on any AP at any time. We are mainly concerned with the ad delivery from APs to commuters, by taking either the broadcast or unicast approach:

1) In the broadcast approach, each AP_k will use its total bandwidth tbw_k to broadcast one ad at a time. In other words, each ad is transmitted using the full bandwidth, and all the commuters in its coverage are the potential receivers.

2) In the unicast approach, each AP_k will use its total bandwidth tbw_k to broadcast *multiple* ads at a time, one for each commuter and each ad consumes a *fractional* bandwidth. Accordingly, bandwidth allocation needs to be handled so that multiple commuters can receive different ads targeted to them at the same time.

Since wireless communication is unreliable, we also assume that: 1) in the broadcast approach, an ad can only be successfully transmitted to a given commuter u_i with some probability, which is inversely proportional to the distance between AP and u_i; 2) in the unicast approach, although customized forward error correction mechanisms can be used such that the targeted ad delivery can always be successful, if AP_k allocates a fraction of its bandwidth to u_i at time t (denoted by $bw_{i,k,t}$), the effective ad transmission bandwidth (denoted by $ebw_{i,k,t}$) is less than $bw_{i,k,t}$, and also inversely proportional to the distance between AP_k and u_i at time t.

E. Problem Statement

The main technical issues of this work are related to ad delivery scheduling and bandwidth allocation (when using the unicast approach). The primary goal of OAD is to send ads to induce commuters to go to shops and buy products. Note that although only the ads received before rcp_{ij} (called the pre-decision ads) can attract u_i to sp_j (as defined in Eq. (1)), the ads received after rcp_{ij} (called the post-decision ads) may or may not bring additional utilities to sp_j. More specifically, on one hand, u_i may decide to purchase additional products due to the post-decision ads, and accordingly, the utilities of the post-decision ads should be counted towards the total realized utility by sp_j and u_i (denoted by $TRU_{i,j}$) in the same way as the pre-decision ads. On the other hand, u_i may have seen enough pre-decision ads and may subsequently ignore the post-decision ads, in which case the post-decision ads bring no additional utility (obviously, the utilities of the ads delivered after u_i arrives sp_j should not be counted). In general, we assume that some $0 \leq \alpha \leq 1$ fraction, where α is called a *utility loss factor* hereafter, of the utilities from the post-decision ads will be counted towards $TRU_{i,j}$ and by default, $\alpha=1$.

Let $V_{i,j}$ be a Boolean variable such that $V_{i,j}=1$ means u_i is successfully attracted by ads to visit sp_j, and 0 otherwise. Let $D_{i,j,h}$ be a Boolean variable such that $D_{i,j,h}=1$ means $ad_{j,h}$ has been delivered to u_i before u_i arrives sp_j; and 0 otherwise. In addition, let $Y_{i,j,h}$ be a Boolean variable such that $Y_{i,j,h}=1$ means $ad_{j,h}$ is a pre-decision ad for u_i; and 0 otherwise. Then, *the total realized utilities* of the delivered ads from sp_j at u_i is

given by:

$$TRU_{i,j} = V_{i,j} \times \left(\sum_{ad_{j,h} \in ads(j)} utl_{j,h} \times \alpha^{Y_{i,j,h}} \times D_{i,j,h} \right) \quad (7)$$

Then, the system-wide total realized utilities, or *TRU*, over all commuters and shops is:

$$TRU = \sum_{i=1}^{n} \sum_{j=1}^{m} TRU_{i,j} \quad (8)$$

The OAD Problem: In a given period *T*, given a number of commuters $\{u_i\}$, shops $\{sp_j\}$, APs $\{AP_k\}$ and Ads $\{ad_{jh}\}$, decide an ad delivery solution such that TRU is maximized.

III. SOLUTION DESIGN FOR OAD

In this section, we will study several solutions using different strategies to address the challenges related to OAD. We begin with a more elaborate discussion on the broadcast *vs.* unicast approach and then propose solutions using broadcast and unicast, respectively.

A. Broadcast vs. Unicast

The broadcast and unicast approaches for ad delivery have their own pros and cons, respectively. For example, compared to unicast, broadcast can result in a less bandwidth usage since multiple commuters can receive an ad in a single broadcast whereas in unicast, in order to deliver the same ad to two commuters for example, two identical copies of the ad have to be transmitted (each using a fractional bandwidth). However, as each ad has different attractiveness to different commuters, broadcast has a weaker ability to customize the ad delivery for each specific commuter, i.e., ad delivery cannot be as targeted as in unicast. For example, if u_1 already decided to visit sp_1, an ad from sp_2 will not have any effect on u_1. So when the same ad is needed only for another user u_2, either because u_2 just moved into the coverage or because u_2 failed to properly receive that previous transmission of the ad, it would be better to use only a fractional bandwidth to send the ad to u_2, so that the remaining bandwidth can be used to send different ads to other users (as done in unicast) instead of using the entire bandwidth to send the ad (as done in broadcast).

Below, we describe the proposed solutions which are based on either broadcast or unicast, starting with straight-forward solutions and culminating in sophisticated ones.

B. Solution Design using Broadcast

One of the key design decisions when using broadcast is to determine which ad will be delivered next. Since ad delivery using broadcast cannot be customized for individuals, an intuitive idea is to design a solution from the shops' standpoint in the sense that the objective is to select an ad which can maximize the total potential utilities at its receivers.

The BRoadcast-based Strategy (*BRS*) works as follows: For a given AP_k, during time $t \in T$, if AP_k currently does not have any on-going transmission, an ad will be selected and broadcasted based on the following three aspects:

Commuter Qualification: Whether an ad's utility can be realized depends on the current status of commuters. For $ad_{j,h}$ from sp_j, a commuter u_i who is currently in AP_k's coverage and can be expected to realize the utility of $ad_{i,h}$ should meet the following two criteria:
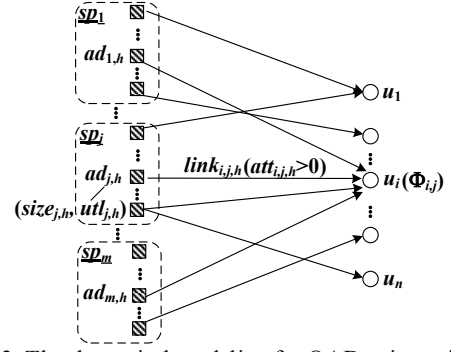

Fig. 3. The theoretical modeling for OAD using unicast

Criteria 1) u_i has never received $ad_{j,h}$. Although an ad can be broadcasted multiple times, only the utility of the ad received by u_i for the first time should count (if/when realized).

Criteria 2) u_i is on the original route to home, and has not passed $rcp_{i,j}$, and accordingly $ad_{j,h}$ is still useful to attract u_i so that she can change route at rcp_{ij} (we denote such commuters by *Type-1 Commuter*). Or, u_i has already decided to visit sp_j at $rcp_{i,j}$ (we denote such commuters by *Type-2 Commuter*).

Clearly, a commuter will change from being a Type-1 Commuter to a Type-2 Commuter when she changes her route at a RCP. Also, there might be other non-qualified types of commuters (e.g., one who has decided to go to a different shop). Hereafter, we denoted the set of all qualified commuters who satisfy the above two criteria by $QC(j,h,k,t)$.

Wireless Resources: BRS also takes into consideration the wireless resource consumptions for broadcasting a specific ad, in terms of the data size of the ad.

Potential Utility: Since multiple commuters can receive the same ad in a broadcast, BRS is also concerned with which ad has the maximum total utilities at all its qualified commuters.

To address the above three aspects, for a given ad $ad_{j,h}$ with utility $utl_{j,h}$ and size $size_{j,h}$, to be delivered by AP_k at time *t*, we define its cost-performance index $\Lambda(j,h,k,t)$ by:

$$\Lambda(j,h,k,t) = \frac{utl_{j,h} \times |QC(j,h,k,t)|}{size_{j,h}} \quad (9)$$

Based on $\Lambda(j,h,k,t)$, AP_k will broadcast the ad having the highest $\Lambda(j,h,k,t)$ (tie-breaking is done by randomly choosing a service in this and all other algorithms studied in this paper).

C. Solution Design using Unicast

a. Graph Theoretical Modeling

When using unicast, the OAD can be transformed to a new graph theoretical problem: Fig. 3 shows a bipartite-graph, the left side is a set of ads from different shops and the right side is a set of commuters. In particular, each $ad_{j,h}$ has two attributes (i.e., $size_{j,h}$ and $utl_{j,h}$), and each u_i has one attribute (i.e., the resistance factor $\Phi_{i,j}$) for each sp_j. There is a directed link between $ad_{j,h}$ and u_i if and only if its attribute, i.e., attractiveness $att_{ij,h} > 0$.

By relaxing some of the earlier assumptions on the shopping decision (See Eqs. (5) and (6) as discussed in Sec. II.C), the OAD problem using unicast becomes that given a total budget of wireless resources (in terms of the totol size of the ads), how to select a set of links in the bipartite graph such that the total utilities of the ads corresponding to these links can be maximized under the following three constraints:

Constraint 1) The total data size of the related ads cannot exceed the total budget;

Constraint 2) For a given commuter u_i, all the selected links related to her come from the same shop. This constraint corresponds to our earlier assumption that a commuter will take detour to only one place/shop (which as mentioned, could be easily extended to include multiple shops in one plaza);

Constraint 3) For a given commuter u_i, and a shop sp_j, the total attractiveness of the selected links is larger than $\Phi_{i,j}$.

To the best of our knowledge, there is no existing problem similar to the above problem, which is different from e.g., the Packing Problem and its variations [18]. It is easy to prove that such a problem is NP-Complete (but the proof is omitted).

b. Pratical Issues and Solution Framework

When using unicast, a practical solution to OAD needs to address the following three issues:

<u>Candidate Shop Selection</u>: Since a commuter could visit at most one shop during her trip home, it is not helpful to deliver ads from multiple shops. Inspired by the Constraint 2) above, we will select one candidate shop for each commuter such that only the ads from that shop will be delivered to the commuter.

<u>Ad Delivery Ordering</u>: After choosing a candidate shop for a given commuter, it is also necessary to decide how to deliver the ads from the chosen shop to this commuter because different ads have different utilities/attractiveness to shops/commuters, respectively.

<u>AP Bandwidth Allocation</u>: Since AP bandwidth is shared between multiple ads/commuters, the total bandwidth of each AP needs to be properly partitioned and allocated.

Note that, for a given commuter, shop selection and ad delivery ordering are done as soon as the commuter starts her trip (i.e., no dynamic shop selection and ad delivery ordering is performed). Below, we will first describe a baseline solution, followed by more sophisticated solutions.

c. BenchMark Strategy (BMS)

This is a baseline solution, which will be mainly used for comparison. For a given commuter u_i, BMS randomly chooses a shop as her candidate shop and the ads from that shop will also be randomly selected for delivery. Note that, even in this baseline solution (as well as other solutions in this section), the current status of the commuters are taken into consideration as done in BRS. More specifically, only the qualified commuters, who meet Criteria 2 as stated in Sec. III.B are considered. Criteria 1 is not necessary anymore because when using unicast, the same ad will not be delivered to a commuter for multiple times.

d. Greedy-Based Strategy (GBS)

GBS solves OAD from the shop's standpoint in the sense that it directly follows the optimization objective. In particular, for a given commuter u_i, GBS chooses sp_j as her candidate shop if the set of the ads having $att_{ij,h} > 0$ from sp_j have the maximum total potential utilities. Then, GBS deliver these ads to u_i in the decreasing order of their utilities, i.e., $utl_{j,h}$. With regard to bandwidth allocation at AP_k, GBS as well as SCS introduced next will split the bandwidth equally among all the qualified commuters in its coverage.

e. Shopping Chance-dominant Strategy (SCS)

In contrast to GBS, SCS looks into the problem from the commuters' standpoint based on the observation that the probability that a commuter decides to visit a shop is inversely proportional to the resistance factor $\Phi_{i,j}$. Accordingly, SCS simply chooses sp_j as u_i's candidate shop if it has the minimum $\Phi_{i,j}$. In addition, Then, SCS deliver these ads to u_i in the decreasing order of their attractiveness, i.e., $att_{ij,h}$, in order to convince u_i to go shopping as quickly as possible.

f. Utility-oriented, Shopping chance and Wireless resources-aware Strategy (USWS)

We propose a holistic solution, called *Utility-oriented, Shopping chance and Wireless resources-aware Strategy (USWS)* in this section. USWS considers both potential utilities and attractiveness of ads when selecting the candidate shop and ad delivery ordering, and also adopts a more intelligent bandwidth allocation scheme.

More specifically, for each AP, we divide its total bandwidth into two parts and the basic idea is to serve/treat different types of commuters (i.e., Type-1 and Type 2 Commuters as defined in the Sec. III.B) differently. This is motivated by the observation that the ads delivered to Type-2 commuters only bring additional utilities to shops while the ads delivered to Type-1 commuters can attract new commuters to shops who may otherwise not do shopping.

In particular, USWS uses a reservation-based policy to allocate the first part of its total bandwidth (say $\beta \times tbw_k$, where β is set to 0.5 in our simulations) for serving Type-1 commuters (so that these commuters can obtain sufficient attractiveness to decide to go shopping). At the same time, USWS uses a contention-based policy to allocate the other part of bandwidth $((1-\beta) \times tbw_k)$ to serve Type-2 commuters to facilitate the delivery of high-utility ads.

With regard to ad delivery ordering, USWS considers the different status of the commuters and the wireless resource consumptions. In particular, assuming that the candidate shop is already selected to be sp_j, USWS will deliver the ads to u_i in the decreasing order of $att_{ij,h}/size_{jh}$ when u_i is still a Type-1 commuter (to maximize the rate of attractiveness accumulation) and in the decreasing order of $utl_{j,h}/size_{jh}$ after u_i changes to a Type-2 commuter (to maximize the rate of utility accumulation).

The candidate shop selection for a given u_i works by examining all the shops one by one as follows: first, pretend that u_i will visit sp_j. Depending on the expected travel speed of u_i to rcp_{ij}, USWS determines the (maximum) amount of available bandwidth of APs (ranging from 0 to $\beta \times tbw_k$) that can be reserved by u_i before passing rcp_{ij} (since it is possible that some bandwidth has already been reserved by other commuters). Accordingly, USWS can also determine the total attractiveness TA_{ij}, (defined in Eq. (1)), and consequently, the probability P_{ij} that u_i can visit sp_j (based on Eq. (6)).

In addition, USWS makes an optimistic assumption that once u_i decides to visit sp_j and passes $rcp_{i,j}$, regardless of the bandwidth contention, u_i can always be allocated bandwidth to the amount of $(1-\beta) \times tbw_k$ from AP_k for receiving other ads from sp_j. Accordingly, USWS can calculate the (maximum) total realized utilities by sp_j and u_i (i.e., TRU_{ij}) as in Eq. (7).Then, USWS calculates the *expected* realized utilities if u_i would visit sp_j (denoted by $ERU_{i,j}$) as follows:

$$ERU_{i,j} = P_{i,j} \times TRU_{i,j} \qquad (10)$$

Finally, USWS will select sp_j having the largest $ERU_{i,j}$ as the candidate shop for u_i. Once the candidate shop is selected,

USWS will formally reserve bandwidth for u_i until she reaches $rcp_{i,j}$ (and changes to Type-2 commuter), and then allocates bandwidth to u_i based on contention, as described earlier. In particular, when serving Type-2 users, all the bandwidth will be allocated to u_i if she is about to receive $ads_{j,h}$, which has the largest $util_{j,h}/size_{j,h}$ among all the ads about to be delivered to other Type-2 users in AP_k's coverage.

Note that the actual amount of bandwidth allocated to u_i will be different from that estimated during the candidate shop selection process. In particular, since u_i will not travel at the speed that exactly matches the expected/estimated speed, AP_k adopts the following elastic bandwidth utilization approach: First, if at time t, u_i does not appear in the coverage of AP_k as expected, her reserved bandwidth will be equally shared by other Type-1 commuters. Second, if there is only one type of commuters in the coverage, all the bandwidth for serving the other type of commuters will also be shared and reused. Using the above elastic bandwidth utilization, sometimes Type-1 commuters may already receive sufficient attractiveness before arriving their RCPs. Therefore, USWS will go one step further by taking a more aggressive strategy: if $SD_{i,j}$ already exceeds $\Phi_{i,j}$ before u_i arriving at $rcp_{i,j}$, USWS will immediately change the ad delivery ordering to the decreasing order of $util_{j,h}/size_{j,h}$, instead of $att_{i,j,h}/size_{j,h}$, in order to maximize the resulting $TRU_{i,j}$.

D. Solution overhead

The solutions using unicast (i.e., BMS, GBS, SCS and USWS) have less overhead than the solution using broadcast (i.e., BRS). This is because in BRS, an ad can be broadcasted multiple times, and therefore, APs have to check all the ads for each transmission. In comparison, in the solutions using unicast, the candidate shop selection and ad delivery ordering procedures for a given commuter can only be executed once, which can significantly reduce the computational overhead and is another advantage of using unicast for ad delivery.

IV. PERFORMANCE EVALUATION

In this section, we evaluate the performance of the proposed solution strategies on a simple, synthetic 8×8 grid road network occupying an area of around 100 km^2, as shown in Fig.4 (a); subsequent sections will describe performance evaluation using real-world vehicle traces (Sec. V) an a detailed microscopic traffic simulator (Sec. VI).

For the grid network, we assume that 20 shops are randomly distributed throughout the network, each having a number of ads to be delivered. We assume that only the ads from three shops would have non-zero attractiveness to a given commuter. In an initial setting, 1000 commuters start their trips during the simulation, and for each commuter, we generate a trip of about 10 km long (which represents a reasonable and realistic travel distance from the workplace to home) and set its origin/source, destination, and the original route from source to destination. Wi-Fi APs for OAD are assumed to be located at a subset of the network intersections. Finally, the travel speeds of the roads are randomly set from 10 to 45 (km/hr) every ten minutes in order to reflect real-world traffic conditions and their dynamic nature. In the simulation, we randomly generate 30 test cases for a given parameter setting. Here, Table I lists

Table I: Default values of experiment parameters

Basic Road Network	8×8 Grid (~100 km^2)
Travel Speeds of Roads	[10km/hr, 45km/hr]
Simulation Time in Each Case	3600s
No. of Total Shops (m)	20
No. of Total Commuters(n)	1000
Maximum Value of $\Phi_{i,j}$	1
No. of Interested Shops Per Commuter	3
No. of Ads from a Shop	200
The Attractiveness/Utility of an Ad	[1, 100]
The Size of a Video-based Ad	[1MB, 10MB]
AP Total Bandwidth	25 Mbps
AP Coverage Range	150m
AP Deployment Percentage at Intersections	30%

different parameters and their default values or values range.

We consider the performance of BMS as our base line and define the *average performance improvement ratio* (*APIR*) of a solution S over BMS as being equal to:

$$APIR = (TRU_S - TRU_{BMS})/TRU_{BMS} \qquad (11)$$

where TRU_S and TRU_{BMS} are the sum of the TRUs obtained by solution S and of BMS over all test cases, respectively.

A. Testing Results

Fig. 5 (a) compares the performances of the four solution strategies to BMS, assuming the default setting. Generally speaking, USWS yields the best performance, which indicates that the proposed holistic approach is useful. Since USWS shows a significantly better performance compared to the second best solution, i.e., BRS, this also seems to indicate that a well-designed approach using unicast can be more efficient for OAD. In comparison, the naïve approaches (GBS and SCS) perform worse than BRS. Here, SCS is still better than GBS, which means that it may be more important to pay attention to commuters' shopping interest and decision making behaviors, instead of just focusing on the utilities of the ads.

Fig. 5 (b) shows the APIR of each solution as the total number of commuters increases. As can be seen, the superiority of USWS becomes more noticeable with more commuters. This is because the limitations on the wireless resources become more significant with more commuters in the system. Because of its sophisticated bandwidth allocation procedure, USWS can more effectively utilize the wireless resources for ad delivery compared to other solutions, e.g. GBS and SCS, which only adopt a straightforward bandwidth allocation mechanism. In addition, since the major advantage of using broadcast (as in BRS) is to save bandwidth, such an advantage becomes more apparent in BRS (although it is still much worse than USWS) when serving more commuters.

Next, we study the effect of the resistance factor $\Phi_{i,j}$. As shown in Fig. 5(c), when the maximum value of $\Phi_{i,j}$ is zero, the performance of USWS is similar to that of other strategies. This is because with a small $\Phi_{i,j}$, it is easier to attract more commuters using any of these strategies than the baseline approach. However, as long as the maximum value of $\Phi_{i,j}$ is larger than 0, USWS performs much better, and the relative improvement of all the approaches over the baseline approach becomes almost constant.

Now Looking at Fig. 5 (d), it can be seen that the APIR of USWS deceases as the AP deployment percentage or density
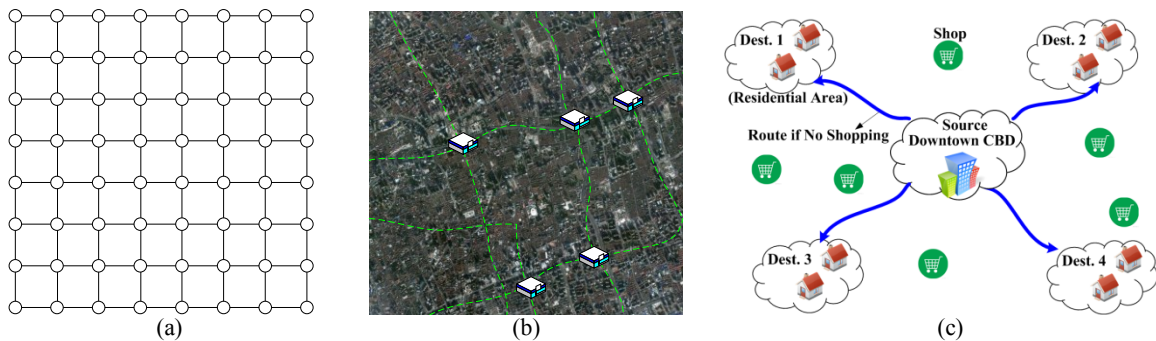
Fig. 4. The scenario and road network (a) In the basic simulation. (b) In the case study. (c) In the traffic simulator (PARAMICS).

increases. This is because in contrast to Fig. 5 (b), wireless resources become less limited when more APs are deployed. Accordingly, the advantage of USWS in terms of its ability to optimally allocate resources becomes less important.

Since USWS performed best in the basic simulation, now we pay closer attention to USWS in the remaining part of this section and the next, and only compare solutions using unicast.

Fig. 5 (e) shows the APIR of USWS increases as the utility loss factor α increases. In particular, when α is 1 as in the default setting (which means the 100% of the utilities of the post-decision ads delivered to Type-2 commuters can be realized), it is worthwhile to use AP bandwidth for serving Type-2 commuters. As α decreases (a special case is when α is set to 0), although USWS can still effectively deliver ads to Type-2 Commuters, its relative performance becomes worse because only a part of the utilities of the post-decision ads delivered can be realized. Still, as observed, USWS has the best performance.

V. CASE STUDY USING REAL-WORLD VEHICLE TRACES

In this section, we evaluate the performance of the OAD solution strategies using a real-world case study from the city of Shanghai. We focus on an area about 9km × 9km (as shown in Fig. 4 (b)) and use real vehicle traces from 1000 taxis within this area, which provide real mobility profile/pattern. For this particular case study, we face the following technical challenge: on one hand, we intend to perform our testing on these real traces without artificially modifying them, and on the other hand, within the context of OAD, commuters are expected to change routes. To deal with this issue, we consider a special case of OAD in which commuters do not have to take any detour from their original routes. This can be achieved by placing all the shops of interest to a commuter along the route to home. Accordingly, we build our testing scenario as follows: we first plot the entire traces and identify the intersections of those traces. We then place a number of shops at the intersections of those traces. To avoid repetition and due to limited space, below, we only present results on the effect of the parameters that have not been considered in the synthetic network earlier.

In Fig. 5 (f), we look at how USWS performs when the number of shops to be visited per commuter varies from 1 to 3. As can be seen, the APIR for USWS increases with the increase in the number of shops of interest. A special case here is when each commuter is only interested in a single shop. In that case, the candidate shop selection function in USWS

becomes useless, which explains why USWS has the least improvement in that scenario.

Fig. 5 (g) shows how AP coverage can affect the value of APIR. We observe that the APIR of USWS decreases as AP coverage increases. The reason is similar to that given with respect to Fig. 5 (d), as in both case, more wireless resources become available.

VI. EVALUATING OAD WITH TRAFFIC SIMULATOR

In this section, we study the OAD problem using an integrated traffic and network simulator in order to 1) use a more realistic traffic model/flow and 2) study the interaction between traffic intensity/congestion on the roads, and shopping activities induced by OAD application. On the traffic side, we use PARAMICS [19], which is a state-of-the-art commercial microscopic traffic simulator (TS). We have integrated PARAMICS with our network simulator (NS) in which OAD has been implemented. Within the integrated simulator, TS provides the real-time vehicle mobility traces to NS, while the OAD agents in the NS send back the shopping/route changes decisions to the TS which in turn simulates the resulting traffic patterns. The use of the TS allows for more realistic simulation of traffic and vehicular behavior (e.g. vehicle acceleration/deceleration/lane changing, and the behavior of traffic lights at intersections).

We focus on a typical scenario that emulates the real-life daily commute patterns in the evening rush hour. In particular, in the scenario shown in Fig. 4 (c), we assume that there is a central working area, e.g., a central business district (CBD), four surrounding residential areas, and twenty shops distributed throughout the network. For the duration of the simulation, commuters (~2000 drivers) gradually start their trip from CBD (i.e., source) towards one of four residential areas (i.e., destinations). Approximately 3500 background vehicles are also injected into the road network.

First, we found USWS still yields the best performance in terms of APIR, a trend which is similar to Fig. 5 (a). Given that the traffic flow/pattern is quite realistic in PARAMICS, this further validates that USWS is practically useful.

Next, we evaluate how OAD affects traffic flow, and how beneficial it is as a possible congestion mitigation strategy. In particular, we simulate two situations: 1) OAD-ON, in which the targeted 2000 commuters may engage in shopping activities on their way home after being attracted by the on-road ads delivery using USWS (we model this by assuming that when commuters arrive at a given shop, they temporarily
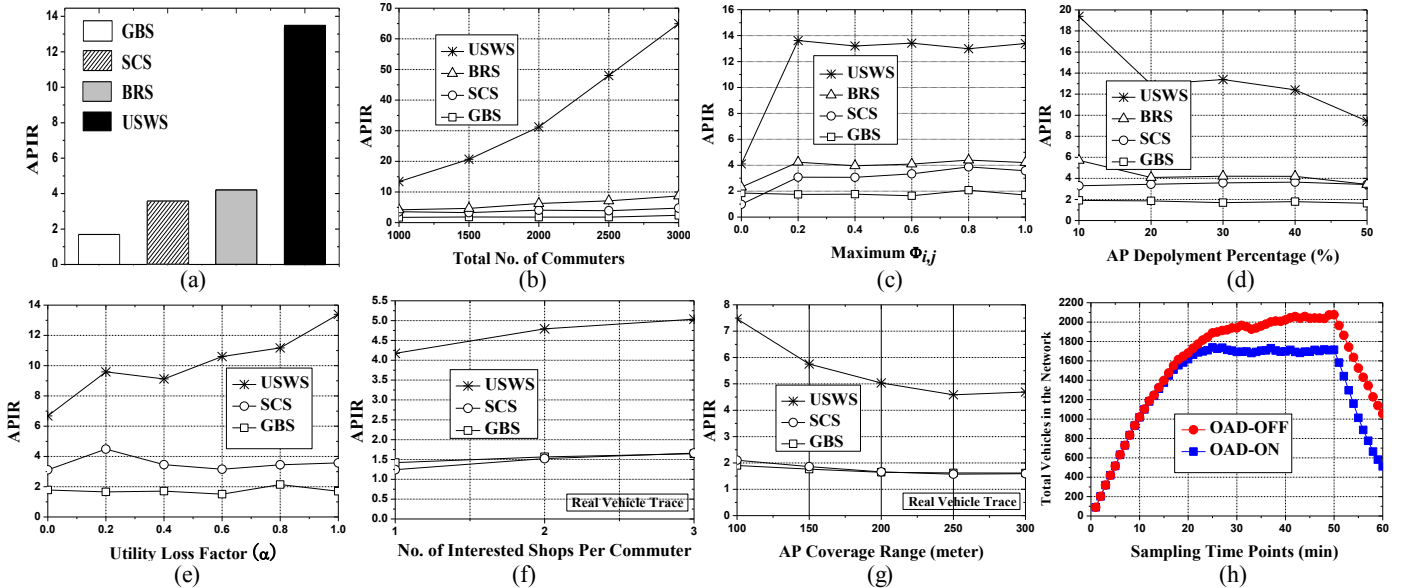
Fig. 5. Testing results. (a) Performances under the default setting. (b) Performances under different commuter number. (c) Performances under different $\Phi_{i,j}$. (d) Performances under different AP deployment percentages. (e) Performances under different α. (f) Performances with real trace under different number of interested shops. (g) Performances with real traces under different AP coverage. (h) The total vehicles in the road network at different sampling time points.

disappear from the road network, for say 10-30 minutes to model the shopping time, and then resume their travel towards their destinations after that time has elapsed); 2) OAD-OFF, in which ad delivery is disabled and all the commuters go home directly without stopping at any of the shops.

It is a well-known fact that traffic congestion during peak periods result from having massive traffic volumes injected into the road network during a short time period. OAD has the potential to serve as a congestion reducing strategy in terms of spreading that peak traffic volume over a longer time period, because individuals may spend some time shopping, before getting back onto the road network (the shops and their parking lots may serve as storage spaces for traffic).

Fig. 5 (h) shows the total number of vehicles in the road network sampled at 12 time points during the one-hour simulation for both the OAD-ON and OAD-OFF scenarios. To better illustrate OAD's effect, here we set the maximum resistance factor $\Phi_{i,j}$ to a small value so that most of the targeted users (our simulation shows that this number is around 1600) can go shopping on their way home. As can be seen, the traffic load first increases as vehicles are injected into the road network and then decreases when most of the vehicles arrive at their destinations. In particular, the traffic load with OAD-ON is always less than that with OAD-OFF since in the former, users may leave the road network for shopping, and therefore, short-term traffic load on the road can be reduced. Such an effect is not that obvious in the first 20 minutes because most users have just started their trips and are traveling towards shops.

Besides the total traffic load on the road network, we also take a look at OAD's effect on the spatial traffic load distribution over the road network's links. Because in the road network generated by PARAMICS, we have assumed that all links have the same capacity, the smaller the variation in traffic volumes across the links, the better. We note down the

traffic volume on each individual link every 5 minutes and also calculate their standard deviations. Fig. 6 (a) shows a typical traffic distribution (in 5 minutes). As can be seen, OAD-ON leads to a more balanced traffic load (indicated by the shaded bars) compared with OAD-OFF. This is because in OAD-ON, for each individual commuter, if the traffic is much heavier on the route home compared to the route to shops, the commuter is more likely to go shopping first. Such an individual shopping behavior actually leads to a system-wide traffic-balancing effect.

In particular, Fig. 6(a) shows that the traffic-balancing effect is more pronounced with the increase in the number of commuters going shopping; in our simulations, we vary that number by gradually increasing the maximum value of $\Phi_{i,j}$ (Note, we can only configure $\Phi_{i,j}$ and cannot exactly control how many users will go shopping in the simulation. This is why the numbers in Fig. 6 (a) are not perfectly spread out).

Lastly, Fig. 6 (b) shows the average travel speed of all the vehicles (i.e., not just the targeted 2000 commuters) sampled at 12 time points. As can be seen, compared to OAD-OFF, vehicles can travel more than 10% faster on the road using OAD-ON. This shows that OAD has the potential to improve traffic conditions in terms of traveling speed, not only for those commuters who go shopping but to the whole traffic system. In addition, if the route directly to home is very congested compared to the detours to shops, it is possible that the total travel time on the detour can be even less than that on the original route home.

VII. RELATED WORK

Several studies in the marketing field have focused on the effects of advertisements on customer behaviors and on-line advertising. However, none of them studied the on-road targeted advertising paradigm, which has its own unique/novel
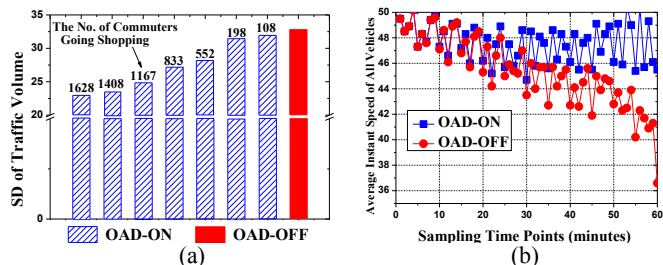
Fig. 6. (a) The standard deviations (SD) of traffic volume during 5 min. (b) The average speeds of all the vehicles at different sampling time points.

characteristics as outlined earlier. For example, the work in [10] presented a theoretical research study on how advertising works. Basically, an advertising model goes through the following states: ad input, customer attention/interest, cognition and then action. The work in [11][12] identified the correlation between purchase intentions and actual purchasing, which is shown to be related to the product attributes, promotion variables, etc. Work in [8] looked into how online advertising differs from traditional advertising.

Existing studies on drivers' human factors related issues have focused on how human drivers could be affected by external factors. For example, works in [3][5] examined how personality, lifestyle and other factors affect driving performance. [4] has looked into the problem of how on-board vehicle systems may improve road safety improvements. However, no existing works studied how to design message delivery protocols to affect human behaviors.

Most of the existing research on VANETs has focused on the traditional networking-related technical issues. Work in [17] demonstrated that AP handoffs can be implemented very efficiently by using predictive methods based on historical information, which can serve as a guide when implementing our own system. Work in [13] studied service scheduling issues for vehicle-roadside data access in VANET and proposed a list of solutions to serve upload and download requests based on their deadline and data size. [18] aimed at defining a theoretical framework to analyze the performance of a vehicular network in the Drive-thru Internet scenario. Also, in all those previous studies, maximizing data throughput has been the major optimization objective.

Other research issues addressed previously include mobility modeling [15], data delivery and access [6], road safety [7], etc. Our previous work [1] accounted for human factors when determining how messages should be scheduled and delivered to maximally benefit the drivers, but did not consider how the human reactions would affect the traffic, i.e., it did not consider the feedback loop between the human element, cyber systems and transportation systems as we did in this work.

VIII. CONCLUSION

Vehicular Cyber-Physical System (*VCPS*) has the ability to improve/enrich trip experience of commuters. In this work, we have proposed a new application called *On-road Ad Delivery* (*OAD*), in which targeted ads are delivered by the road-side APs to commuters in order to induce them to shop during their trips to home for example. The main challenges as well as

novelties of such an application come from the fact that the attractiveness of the ads, the length of the detour to shops, and the current and expected future traffic conditions can affect commuters' shopping decisions, and therefore, we need to consider not only the human elements, the cyber system, and the transportation systems, but also their interactions. In this paper, we have formulated a new optimization problem in OAD, which is mainly concerned with ad delivery scheduling and AP bandwidth allocation with the objective being to maximize the *total realized utilities* (*TRU*) of the delivered ads. We have also designed a number of efficient solutions and presented a comprehensive performance evaluation and comparison study, utilizing both the real traces from the city of Shanghai, as well as a state-of-the-art traffic simulator called PARAMICS. We have also shown that OAD has transportation-related benefits in terms of balancing road traffic and alleviating congestion.

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