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Implementation of DORA: Dynamic Optimal Random Access for Vehicle-to-Roadside Communications

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Abstract

In DORA, we study random access in a drive thru scenario, where roadside access points (APs) are installed on a highway to provide temporary Internet access for vehicles. We consider Vehicle-to-Roadside (V2R) communications for a vehicle that aims to upload a file when it is within the APs' coverage ranges, where both the channel contention level and transmission data rate vary over time. The vehicle will pay a fixed amount each time it tries to access the APs, and will incur a penalty if it cannot finish the file uploading when leaving the APs. First we improved the optimization and created backbone for every network. Then we consider the problem of finding the optimal transmission policy with a single AP and random vehicular traffic arrivals. We create a finite-horizon sequential decision problem, solve it using Dynamic Programming (DP), and design a general, Dynamic Optimal Random Access (DORA) algorithm. We derive the conditions under which the optimal transmission policy has a threshold structure, and propose a monotone DORA algorithm with a lower computational complexity for this special case. Next, we consider the problem of finding the optimal transmission policy with multiple APs and deterministic vehicular traffic arrivals thanks to perfect traffic estimation. We again obtain the optimal transmission policy using DP and propose a joint DORA algorithm. Simulation results based on a realistic vehicular traffic model show that our proposed algorithms achieve the minimal total cost and the highest upload ratio as compared with some other heuristic schemes. In particular, we show that the joint DORA scheme achieves an upload ratio 170% and 257% better than the heuristic schemes at low and high traffic densities.

Keywords: *Random access, Medium Access Control (MAC), Vehicular Ad hoc networks, dynamic programming, Markov decision Processes, threshold policy*.

1. Introduction

Vehicular Ad hoc Networks (VANETs) enable autonomous Data exchanges among vehicles and roadside Access Points (APs), and are essential to various Intelligent Transportation System (ITS) applications. For example, safety applications (such as cooperative forward collision warning, lane change warning, and left turn assistant and Engineering Research Council (NSERC) of Canada ,proposed to improve the safety of the passengers by informing the vehicles of potential dangers ahead of time. Non-safety applications (such as traffic management, instant messaging, and media content delivery) have been designed to avoid traffic congestion and improve the experience of driving. Clearly; the Quality of Service (QoS) requirements of various applications is different. VANETs support various ITS applications. Through different types of communication mechanisms, including Vehicle-to Roadside (V2R) and Vehicle-to- Vehicle (V2V) communications. V2R communications involve data transmissions between vehicular nodes and roadside APs.

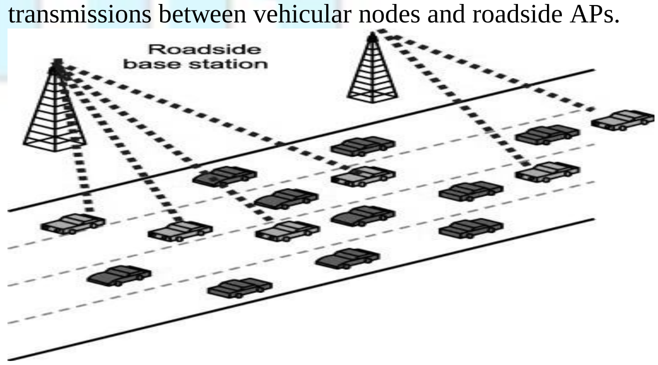

Fig 1.general vehicle to roadside communication.

V2V communications only involve data exchanges among vehicular nodes. For both types, we can further classify the communications as either single hop or multi-hop. In this paper, we focus on analyzing *V2R* ***single-hop uplink transmissions*** from vehicles to APs. Due to the limited communication opportunities between vehicles and APs, efficient resource allocation (either centralized or distributed) is crucial for the successful deployment of V2R ITS applications. In the *centralized* setting, the AP schedules the transmissions from different vehicles based on some predefined criteria. Hadaller proposed a scheduling protocol that grants channel access to a vehicle that achieves the maximum transmission rate. Analytical and simulation results showed significant overall system throughput improvement over a benchmark scheme. We considered the case where roadside APs only store the data uploaded by the vehicles. Scheduling priority is determined by two factors: data size and deadline. A request with either a smaller data size or an earlier deadline will be served first. Alcatraz *et al.* in considered both uplink and downlink scheduling of non real- time traffic for non-safety applications. The scheduling problem was formulated as a constrained linear quadratic regulator design problem that aims to reduce the residual queue backlog for each user. However, because centralized resource allocation is not scalable due to its computational complexity, we focus on distributed resource allocation scheme in this paper. In the *distributed* setting, the vehicles contend for the channel for transmission based on the applications QoS requirements. Shrestha *et al.* in considered the scenario where the data packets are first distributed from the Road Side Units (RSUs) to the On Board Units (OBUs). The OBUs then bargain with each other for the missing data packets, and exchange them using Bit Torrent protocol. Jarupan *et al.* in proposed a cross-layer protocol for V2R multi-hop communication. The Medium Access Control (MAC) local data traffic and the routing module find a path with the Minimum delay. The optimal pricing and bandwidth reservation of a service provider is obtained using game theory, and the optimal download policy of an OBU is obtained using constrained Markov decision processes. We analyzed the performance of a downlink resource allocation scheme in a V2R communication

System with one AP on a road. The distribution of the number of bytes downloaded per drive-thru was derived using Markov reward processes. Later we proposed a cross-layer protocol in the physical and MAC layers that addresses the issues of channel fading, synchronization, and channel contention. Performance analysis was presented for the channel contention scheme, and a test bed was used to evaluate the proposed protocol. In this paper, we aim to design a *uplink* random access algorithm that is *distributed* in nature, so that it is compatible with the IEEE 802.11p standard that is developed to facilitate the provision of wireless access in vehicular environment different from most previous works on *heuristic* distributed uplink V2R communication algorithm design, we aim at designing an *optimal* uplink resource allocation scheme In VANETs analytically in this paper. In this work, we consider the drive-thru scenario where vehicles pass by several APs located along a highway and obtain Internet access for only a limited amount of time. We assume that a vehicle wants to upload a file when it is within the coverage ranges of the APs, and needs to pay for the attempts to access the channel. As both the channel contention level and achievable data rate vary over time, the vehicle needs to decide when to transmit by taking into account the required payment, the application's QoS requirement, and the level of contention in current and future time slots. Because of the dynamic nature of the problem, we formulate it as a finite horizon Sequential decision problem and solve it using the Dynamic Programming (DP). The main contributions of our work are as follows:

Optimal Access Policy Design**:** In the case of a single AP with random vehicular traffic, we propose a general Dynamic Optimal Random Access (DORA) algorithm to compute the optimal access policy. We further extend the results to the case of multiple consecutive APs and propose a Joint DORA (JDORA) algorithm to compute the optimal policy.

Low Complexity Algorithm**:** We consider a special yet practically important case of a single AP with constant data rate. We show that the optimal policy in this case has a threshold structure, which motivates us to propose a low complexity and efficient monotone DORA algorithm.

Superior Performance**:** Extensive simulation results show that our proposed algorithms achieve the minimal total cost and the highest upload ratio as compared with three other heuristic schemes. In the multi-AP scenario, the performance improvements in upload ratio of the JDORA Schemes are 130% and 207% at low and high traffic densities, respectively. The rest of the paper is organized as follows. We describe our system model in Section II and formulate the DP problem Fig. 1. Drive-thru vehicle-to-roadside (V2R) communications with multiple APs.

2. System Model

We consider a drive-thru scenario on a highway as shown in Fig. 1, where multiple APs are installed and connected to a backbone network to provide Internet services to vehicles within their coverage ranges. We focus on a vehicle that wants to upload a *single* file of size S when it moves through a segment of this highway with a set of APs $J = \{1, . . . , J\}$, where the vehicles pass through the ith AP before the jth AP for $i < j$ with $i, j \in J$. We assume that the jth AP has a transmission radius Rj . We also assume that the vehicle is connected to at most one AP at a time. If the coverage areas Of the APs are overlapping, then proper handover between the APs will be performed. For the case of exposition, we assume that the APs are set up in a way that any position in this segment of highway is covered by an AP. Our work can easily be extended to consider the settings where the coverage areas of adjacent APs are isolated from each other.

2.1 Traffic Model

Let λ denote the average number of vehicles passing by a fixed AP per unit time. We assume that the number of vehicles moving into this segment of the highway follows a Poisson process with a mean arrival rate λ. Let ρ denote the vehicle density representing the number of vehicles per unit Distance along the road segment, and v be the speed of the vehicles. From we have $\lambda = \rho v$. (1)The relation between the vehicle density ρ and speed v is given by the following equation $v = vf\,(1 - \rho/\rho max)$, (2) where vf is the free flow speed when the vehicle is moving on the road without any other vehicles, and ρmax is the vehicle density during traffic jam.

2.2 Channel Model

Wireless signal propagations suffer from path loss, shadowing, and fading. Since the distance between the vehicle and the AP varies in the drive-thru scenario, we focus on the dominant effect of channel attenuation due to path loss. The data rate at time slot t is given by $wt = W$ log2 1 + $PN0Wd\gamma t$, (4) where W is the channel bandwidth, P is the transmit power of the vehicle, dt is the distance between the vehicle and the closest AP at time slot t, and γ is the path loss exponent. We assume that the additive white Gaussian noise has a zero mean and a power spectral density $N0/2$. In addition, we also consider a special case with fixed data rate.

2.3 Distributed Medium Access Control (MAC)

We consider a slotted MAC protocol, where time is divided into equal time slots of length Δt. We assume that there is perfect synchronization between the APs and the vehicles with the use of global positioning system (GPS) The total number of time slots that the vehicle stays within the coverage range of the jth AP is Tj =2Rj $v\Delta t$ We use the notation $\zeta(j, \tau)$ to denote the τth time slot when the vehicle is in the coverage area of the jth AP, i.e., $\zeta(j, \tau)$ = _j−1 i=0 $Ti + \tau$, $\forall$ $\tau \in \{1, . . . , Tj\}$, (5) where $T0$ = 0. The set of time slots in the jth AP with respect to this time line representation is $Tj = \{\zeta(j, 1), . . . , \zeta(j, Tj)\}$. An example of the time line representation is given in when the vehicle first *enters the coverage range* of the jth AP, it declares the type of its application to the AP. In return, the jth AP informs the vehicle the channel contention in the coverage range (λ and $psucc\ t$, $\forall$ $t \in Tj$), data rate in all the time slots in the jth coverage range (i.e., wt, $\forall$ $t \in Tj$), the price qj , and the estimated number of vehicle departures from The structure of a time slots of the jth AP. the coverage range in all the time slots in the jth coverage range (i.e., lt, $\forall$ $t \in Tj$). We further elaborate these system parameters as follows: $psucc\ t$ represents the probability that the vehicle can successfully obtain access in time slot $t \in Tj$ after contending with all the vehicles in the jth coverage range. $Psucc\ t$ is estimated by the AP based on the level of system contention and it varies over time. Since $psucc\ t$ is related to the number of vehicles nt currently in the jth coverage range at time slot t, we define $psucc\ t = gj(nt)$, where gj is a strictly decreasing function. An AP knows the value of nt, since vehicles need to establish and terminate their connections when they enter and leave the coverage range, respectively. $qj \geq 0$ denotes the amount a vehicle needs to pay the AP for each time slot that it sends a transmission request in the jth coverage range, even it fails to access the assigns the time slot to one of these vehicles. The vehicle, which receives the acknowledgement (ACK), can transmit the data packets in the remaining time $\Delta tdata$ of this time slot, where $\Delta tdata < \Delta t$. The structure of a time slot is. Meanwhile, regardless of which vehicle is granted the time slot, each vehicle which requested to transmit in the time slot needs to pay qj to the jth AP. Without such pricing, each vehicle would send a request in every time slot, which unnecessarily increases the contention level and prevents efficient allocation of time slots to the most needed application. The vehicle aims to achieve a good *tradeoff* between the total uploaded file size and the total payment to the Aps according to the QoS requirement of the application. For example, a higher priority may be placed on the total uploaded file size for safety applications, but on the total payment for non-safety applications. The problem is further complicated by the time varying data rate wt and channel contention level. Therefore, it is a challenge for the vehicle to decide when to request for data transmission.

3. Finite-Horizon Dynamic Programming

In this section, we describe how to obtain the optimal transmission policies in both the single-AP and multiple-AP scenarios using *finite-horizon dynamic programming*. We first study the single-AP scenario with random vehicular traffic arrival in Section. In particular, we consider a special case that the optimal policy has a *threshold structure* in Section IV-A1. When the traffic pattern can be estimated accurately, we consider a joint AP optimization in Section *A. Single AP Optimization with Random Vehicular Traffic* since we are considering one AP (i.e., $J = \{1\}$) in this sub section, we drop the subscript j for simplicity. Although the exact traffic pattern (i.e., the exact number of vehicles in the coverage range of the AP in each time slot) is not known, the vehicles arrive according to a Poisson process with parameter λ. Meanwhile, the parameters lt ($\forall\ t \in T$), ρmax, Δt, R, and the function $g(\cdot)$ are available. The transition probability of $psucc$ is given by where $\varphi t(n)$ = _$Nmax-n+lt+1$ $y=0$ $(\lambda\Delta t)y$ $y!$ is a normalization factor. Because $psucc = g(n)$ is a strictly decreasing function of n, there is a one-to-one mapping between $psucc$ and n as shown in the first two equalities in. The expression after the third equalities describe the probability with $n\_-n+lt+1$ arrival due to the Poisson process and $lt+1$ deterministic departure at time $t+1$. $n\_$ is lower-bounded by $n-lt+1 \geq 0$ when there is no vehicle arrival, and is upper-bounded by $Nmax$. In this subsection, since we consider $J = \{1\}$, we can simplify problem Let $vt(s, psucc)$ be the minimal expected total cost that the vehicle has to pay from time t to time $T+1$ when it is in the coverage range, state (s, $psucc$) immediately before the decision at the time slot t ϵ T. The optimal equation 17 & 18 relating the expected total cost at different states for t>T is vt(s).

$$v_t(s, p^{succ}) = \min_{a \in \mathcal{A}} \{\psi_t(s, p^{succ}, a)\}, \tag{16}$$

where

$$\psi_t(s, p^{succ}, a) = c_t(s, p^{succ}, a) + \sum_{s' \in \mathcal{S}} \sum_{p^{succ'} \in \mathcal{P}} p_t((s', p^{succ'}) \mid (s, p^{succ}), a) v_{t+1}(s', p^{succ'}) \tag{17}$$

$$= aq + \sum_{p^{succ'} \in \mathcal{P}} p_t(p^{succ'} | p^{succ}) \Big[ap^{succ} v_{t+1}([s - w_t \Delta t_{data}]^+, p^{succ'}) + (1 - ap^{succ}) v_{t+1}(s, p^{succ'}) \Big]. \tag{18}$$

The first and second terms on the right hand side of are the *immediate cost* and the *expected future cost* in the remaining time slots in the coverage range for choosing action a, respectively. Equation follows directly by evaluating using time $t = T + 1$, we have the boundary condition that

$$v_{T+1}(s, p^{succ}) = \hat{c}_{T+1}(s, p^{succ}) = h(s). \tag{19}$$

Lemma 1: **The value of $\psi_t(s, p^{succ}, a)$, $\forall t \in \mathcal{T}$, can be obtained as**

$$\psi_t(s, p^{succ}, a) = aq + \sum_{m=0}^{N_{max}-n+l_{t+1}} \frac{(\lambda \Delta t)^m}{m! \phi_t(n)} \times \Big[ap^{succ} v_{t+1}([s - w_t \Delta t_{data}]^+, g(n + m - l_{t+1})) + (1 - ap^{succ}) v_{t+1}(s, g(n + m - l_{t+1})) \Big], \tag{20}$$

vehicles in the coverage range of the AP. *Proof:* The result follows directly by evaluating Intuitively, the minimal expected

cost $vt(s, psucc)$ should be smaller when the remaining file size s to be uploaded is smaller. It is confirmed by the following lemma: *Lemma 2:* $vt(s, psucc)$ is a non decreasing function in s, $psucc$ P, t T .

4. Performance Evaluations

In this section, we first compare algorithms 1 and 3 with three heuristic schemes using the traffic model described in Section 2. in both the single-AP and multiple-AP scenarios. In particular, we study the performance of algorithm 3 under imperfect estimations of the $psucc\ t$ in the multiple-AP scenario. We then study the threshold policies obtained by algorithm share the channel with an equal probability. Therefore, $psucc\ t = 1/nt$. The third heuristic scheme is the MAC protocol in the multi-carrier burst contention (MCBC) scheme similar to the greedy scheme Otherwise, packet collision will occur. For the evaluations of all the schemes, we use the convex self-incurred penalty function h(s) = bs2, where b≥0 is a constant. The simulation parameters are listed in Table I. We first study the impact of penalty parameter b on the total uploaded file size for S = 100 Mbits and ρ = 20 veh/km in one AP.

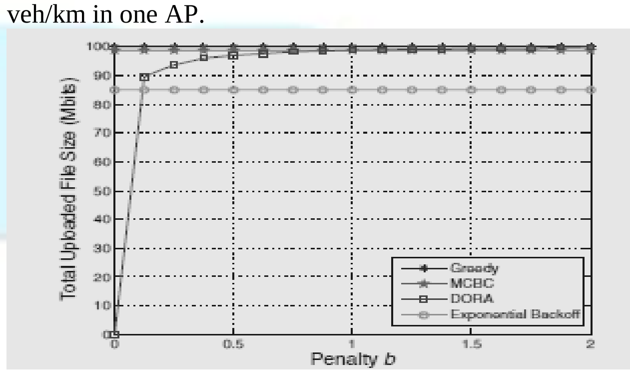

Fig. 1, by increasing b, a larger penalty Penalty b Total Uploaded File Size (Mbits) Greedy MCBC,DORA Exponential Backoff Total uploaded file size against the penalty parameter b for S = 100 Mbits and ρ = 20 veh/km with a single AP.

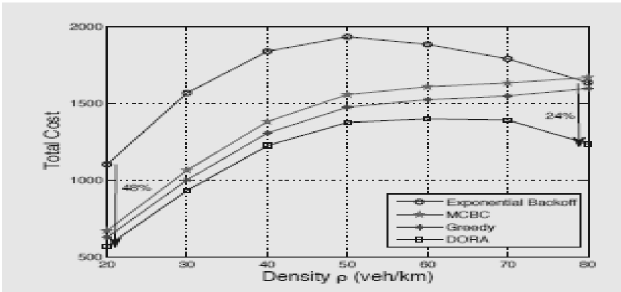

Fig. 2. Total cost versus traffic density ρ for file size S = 200 Mbits with a single AP.The DORA scheme has the minimal total cost is incurred on the size of the file not yet uploaded by using algorithm 1. As a result, a larger file size is uploaded to reduce the penalty. Depending on the QoS requirements of different applications, different values of b should be chosen that tradeoff the total uploaded file size and total payment to the AP by a different degree. Taking safety application as an example, it may be more important to maximize the uploaded file size than to reduce the total payment to the APs, so a large value of b should be chosen. Their total uploaded file size is independent of b. Next, we plot the total cost against the traffic density ρ for S = 200 Mbits with b = 0.1 for the case of one AP in. It is clear that the DORA scheme in Algorithm 1 achieves the minimal total cost as stated in theorem 1, with 48% and 24% cost reduction as compared with the exponential Backoff scheme at low and high ρ, respectively. To measure the cost effectiveness of the file uploading for the four schemes, we propose a metric called the *upload ratio*, which is defined Density ρ (veh/km) Upload Ratio. DORA Exponential Backoff Greedy MCBC 17%.

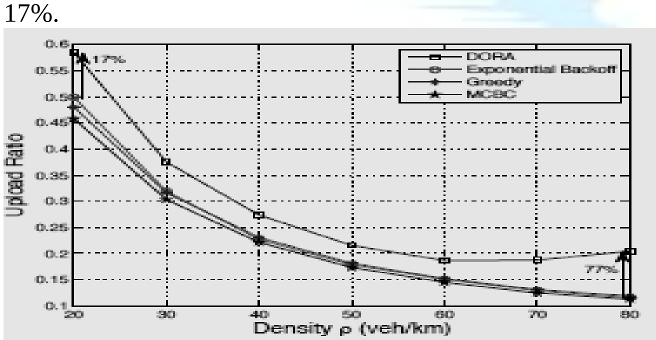

Fig. 3. Upload ratio (i.e., total uploaded file size / total payment to the APs) versus traffic density ρ for file size S = 200 Mbits with a single AP.The DORA scheme achieves the highest upload ratio. Density ρ (veh/km) Total Cost MCBC Greedy Exponential Backoff JDORA (θ = 2) JDORA (θ = 1) JDORA (Perfect Estimation) 71%, 53%.The JDORA scheme with perfect estimation of *psucct* has the minimal total cost. Moreover, a higher total cost is required when the precision of the estimation reduces (i.e., when the variance of the estimation θ increases). as the total uploaded file size divided by the total payment to the APs. In other words, it represents the size of the file uploaded per unit payment. Since the DORA algorithm takes into account the varying channel contention level and data rate in determining the transmission policy, it is cost effective and achieves the highest upload ratio.

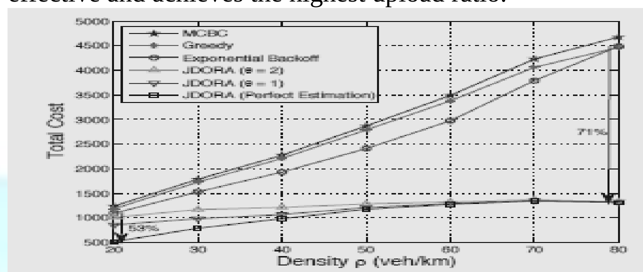

Fig.4. Total cost versus traffic density ρ for file size S = 500 Mbits with five Aps.

In particular, the performance gains in upload ratio over the exponential Backoff scheme are 17% and 77% at low and high ρ, respectively. Furthermore, we consider the case with five APs, where we assume that all of them have the same transmission radii R and price q. For the JDORA scheme in Algorithm 3, we consider that the estimated number of vehicles ˜*not* at time $t \in$ T is obtained by rounding off a normally distributed random variable with a mean *nt* and a variance θ to the nearest nonnegative integer. Thus, the lower the variance θ, the higher is the precision of the estimation. The value of *psucc t* is obtained by setting *psucc t* = *gj*(˜*nt*), ∀ $t \in$ *Tj*, $j \in$ *J*. We plot the total cost and upload ratio in Figs. 7 and 8 for S = 500 Mbits with Density ρ (veh/km) Upload Ratio JDORA (Perfect Estimation) JDORA (θ = 1) JDORA (θ = 2) Exponential Backoff Greedy MCBC 130% 207%. Upload ratio versus traffic density ρ for file size S = 500 Mbits with five APs. The JDORA scheme with perfect estimation of *psucc T* achieves the highest upload ratio as compared with three other heuristic schemes. Moreover, a lower upload ratio is achieved when the precision of the estimation reduces (i.e., when the variance of the estimation θ increases). b = 0.01, respectively is less sensitive to the estimation error when the traffic density ρ is high. It suggests that the JDORA algorithm is suitable especially for VANETs with high traffic densities. Finally, we study the threshold policy in a single AP obtained by Algorithm 2 when the penalty function $h(s)$ is convex and data rate *wt* is fixed. We consider that S = 100 Mbits, v = 100 km/hr, *wt* = 54 Mbps, ∀ $t \in T$, and $h(s)$ is defined as in (27). From Theorem 2, we know that the optimal policy has a threshold structure. In Fig. 9, we plot the thresholds *s*∗ *t* (*psucc*) of the optimal policy against the decision epoch t for different values of *psucc*. With the use of the convex penalty function, we can see that the threshold increases with t. In Fig. 9(a), for b = 0.1, we can observe that the threshold increases when *psucc* decreases. It is because a small penalty parameter is chosen, which places a higher priority on the total payment than on the uploaded file size. When *psucc* is small, the chance of successful transmission is low, so the vehicle chooses a higher threshold and transmits less aggressively to reduce the amount of payment we choose a larger penalty parameter b = 10 such that a higher priority is placed on the uploaded file size than on the total payment. We can observe that the threshold decreases when *psucc* decreases. It is because when *psucc* is small, the vehicle needs to transmit more aggressively.

5. Conclusion

In this paper we used V2R uplink and downlink transmission from a vehicle to the APs in a dynamic drive-thru scenario, where both the channel contention level and data rate vary over time. Depending on the Traffic and usage of transmission can achieve different levels of tradeoff between the total uploaded file size and the total payment to the APs by tuning the self incurred penalty. We proposed a DORA algorithm based on DP to obtain the optimal transmission policy for the vehicle in a coverage range. First we improved the optimization and created backbone for every network. Then we consider the problem of finding the optimal transmission policy with a single AP and random vehicular traffic arrivals. We prove that if the self incurred penalty function $h(s)$ is convex and the data rate *wt* is non-adaptive and fixed, then the optimal transmission policy has threshold structure. Next, for multiple APs with known vehicular patterns, we considered the transmission policy in multiple coverage ranges jointly and proposed an optimal JDORA algorithm. Simulation results showed that our schemes achieve the minimal total cost and the highest upload ratio as compared with three other heuristic schemes. An interesting topic for future work is to consider joint AP optimization without traffic pattern estimation.

Acknowledgments

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