Intelligent Interface Switching among Heterogeneous Wireless Networks for Vehicular Communications

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Abstract—As future vehicular communications will most likely involve multiple wireless networks, intelligent interface switching is of essential importance to support various user preferences across different performance metrics. In this paper, we present a general optimization framework for solving the interface switching problem, and develop a flexible and efficient solution based on stochastic dynamic programming (SDP). Our framework is designed to accommodate different performance metrics such as data transfer efficiency, monetary cost, and interface switching overhead. Accordingly, the proposed SDP-based policy can easily adapt its decision based on user-specified relative importance of the various metrics. Simulation study confirms the optimality of the SDP-based policy over a range of user preference choices, and shows that it consistently outperforms several heuristic schemes.

Index Terms—vehicular communications, interface switching, heterogeneous networks, stochastic dynamic programming (SDP)

I. INTRODUCTION

With the sharp increase of vehicles on roads in the recent years, driving has not stopped from being more challenging and dangerous. Roads are saturated, safety distance and reasonable speeds are hardly respected, and drivers often lack enough attention. Without a clear signal of improvement in the near future, leading car manufacturers decided to jointly work with national government agencies to develop solutions aimed at helping drivers on the roads by anticipating hazardous events or avoiding bad traffic areas. One of the outcomes has been a novel type of wireless access called Wireless Access for Vehicular Environment (WAVE) dedicated to vehicle-to-vehicle and vehicle-to-roadside communications. While the major objective has clearly been to improve the overall safety of vehicular traffic, promising traffic management solutions and on-board entertainment applications are also expected by the different bodies (C2CCC, VII, CALM) and projects (VICS4, CarTALK 2000 [1], NOW5, CarNet, FleetNet [2]) involved in this field.

When equipped with WAVE communication devices, cars and roadside units form a highly dynamic network called a Vehicular Ad Hoc Network (VANET), a special kind of Mobile Ad Hoc Networks (MANETs). In VANETs, vehicles are connected to the Internet through wireless infrastructures via advanced wireless routers, usually named on-board units (OBUs). These OBUs operate seamlessly across multiple wireless interfaces (e.g., WiFi, 3G, and 4G) to different wireless networks (e.g., 802.11a/b/g, 3G, and 802.16e or WiMax [3]), forming a WLAN/Cellular type of vehicular network [4] for data communication between in-vehicle devices (e.g., laptops and smartphone) and the Internet. The support for many interfaces on the OBUs is called multihoming. This technology keeps the end-to-end connection alive as a multi-homing node can leverage multiple access networks through its different interfaces. It provides numerous technological benefits, ranging from opportunistic connection, throughput improvement, load balancing, path resiliency, to fault tolerance.

While much research work have been done on maintaining the end-to-end connection using multiple interfaces, this paper focuses on intelligent interface switching based on OBUs’ requirements of performance and cost. More specifically, given the different performance characteristics of different wireless technologies, what is the desirable switching outcome for OBUs to offer a user-tailored balance between reducing monetary cost and improving communication quality? For example, consider Alice and Bob, who are both passengers on a city bus that is equipped with an OBU with two external wireless interfaces: 3G and WiFi. While the 3G network is largely pervasive, the WiFi network is sparsely deployed. However, 3G networks charge users a fee for data transfer whereas WiFi networks are free. Alice and Bob are both connected to the Internet through the OBU, but Alice is streaming a video for work purposes whereas Bob is downloading a personal file. In this case, communication quality may be more important to Alice than monetary cost, and vice versa for Bob. Ideally, the OBU should allow Alice and Bob to set personal preferences regarding various performance metrics, and then automatically select the best wireless interface for each user based on their preference specification.

In general, the wireless interface selection algorithm can be cast within a multi-objective optimization framework that incorporates any number of user-defined performance metrics. The system then attempts to strike a balance between these terms. By adjusting the weighting factor on each term, the user or OBU designer can influence the behavior of the OBU to achieve the desired tradeoff. Moreover, the weighting factors can be easily updated to reflect the user’s change of interest over time.

In this paper, we present a user-policy driven and multi-factor optimized method for OBU’s wireless interface selection between a 3G link and a WiFi link. This formulation provides a first practical and elucidating example of intelligent, user-policy driven interface selection in a vehicular environment. The performance metrics under consideration are monetary cost, data transfer efficiency, and interface switching overhead. The proposed interface selection algorithm takes into account of future wireless connection possibilities through a stochastic dynamic programming (SDP) framework. The explicit focus on user preferences and future AP encounter prediction distinguishes our approach from other work on heterogeneous wireless network handovers or vertical handoffs. Our formulation, while simple, is directly applicable to real OBU deployments in the near future where the deployment of road-side APs is sparse. The formulation can be easily extended to account for any number of parameters, interfaces, users, performance metrics, and deployment scenarios.

Simulation study of the proposed SDP-based policy confirms its optimality. It is shown that the scheme can achieve the best tradeoff between monetary, data, and overhead performance without the computational demand of exhaustive search. Unlike heuristic schemes which are suitable for only specific scenarios, the SDP approach is able to adapt its policy according to user specified preferences, thereby consistently achieving the best tradeoff among all performance metrics. The rest of the paper is organized as follows. In Section II, we review related work on interface switching among heterogeneous wireless networks and highlight the difference of our approach. Section III provides an architecture overview of our design of the vehicle OBU for hosting the interface switching algorithm. In Sections IV and V, we explain in detail our system

1WiFi access point (AP) locations and performance statistics may be known a priori or can be obtained using crowd-sourcing where AP locations and performance characteristics are reported to a cloud server by passing vehicles. Over time, statistics on different APs, together with GPS location of vehicles, trajectory, and street maps, can be used to predict future WiFi AP encounters.
model, as well as how we formulate the interface switching problem within a stochastic dynamic programming framework. Section VI presents simulation study of the proposed SDP-based policy. Finally, Section VII concludes the paper and discusses the future work.

II. RELATED WORK

In [5], the authors describe a multi-homed mobile access router (MAR) for on-the-move Internet access. MAR is capable of aggregating multiple wireless access links for seamless handoff, throughput improvement and fault tolerance. While MAR is capable of utilizing different wireless links, there lacks a comprehensive, user-policy driven interface selection mechanism. Our interface selection algorithm fills that void. More broadly, our optimization framework is independent of the underlying mobility protocol and can be used for MAR or other systems using other mobility protocols such as Mobile IP (MIP).

In [6], the authors investigate WiFi augmentation of 3G in mobile environments for data offloading. Data is transmitted on WiFi instead of 3G whenever WiFi and predicted future WiFi encounters can satisfy the delay requirement of the application; otherwise, data is transmitted on 3G only. This fixed interface selection strategy does not account for user preferences over different wireless link attributes. Our proposed interface selection algorithm addresses this deficiency and enables dynamic strategy selection. Other work on vertical handoff, such as [7]–[13] and references cited within, lacks user-specified preference input, or performs one-time optimization that fails to account for future AP encounters, or relies on fixed interface switching strategies.

The closest to our work are [14] and [15]. In [14], the authors propose a utility maximization framework for interface selection. User location and trajectory information are used to predict the duration a user stays in the coverage area of one AP. In contrast to our work, this does not take into consideration of future AP encounters. In [15], the interface switching problem is also cast into the Markov decision process formulation. A value iteration algorithm is applied to compute a stationary policy for total expected reward maximization. While the spirit of multi-criteria cost optimization is similar to our work, a key difference lies in when decisions are made. In their work, it is assumed that 3G and WiFi periodically send information from collocated coverage areas. In this way, the interface selection decision is calculated rather frequently at periodic intervals. In the vehicular environment that we are concerned with, WiFi APs are sparsely deployed, hence periodic decision-making becomes impractical. We therefore consider the formation where the selection is made whenever a WiFi AP is encountered, thereby greatly reducing computational complexity.

III. ARCHITECTURAL OVERVIEW

Figures 1 and 2 provide an architectural overview of the connected vehicle environment. We envision the presence of network controllers to act as proxies between the clients on the vehicles and the data center services over the Internet. Road side units (RSUs) can be deployed to augment existing wireless access networks, most likely in a heterogeneous fashion, involving 3G, WiFi, and/or WiMax. Furthermore, the vehicles will be equipped with OBUs, which are capable of pooling together connections over multiple wireless network interfaces and dynamically assigning application packets to one of the available interfaces.

The key components in the OBU are shown in Fig. 3.

- The user preference selection module tracks user-specified preference among various performance metrics for each application flow.
- The mobility manager is in charge of providing seamless connection across various underlying network interfaces.
- The interface manager module takes into consideration communication quality over each interface in terms of available bandwidth and expected duration over that link. It also calculates the optimal interface switching policy based on the statistics over each access network, and decides on the fly which interface to use for each application flow whenever there is a change in the underlying set of available network interfaces.

Fig. 1. Overview of future Vehicle-to-Infrastructure (V2I) architecture. The presence of road side units (RSUs) and network controllers helps to bridge the connection gap between clients inside vehicles and data center services over the Internet.

Fig. 2. System architecture of the connected vehicle environment. An on-board unit pools together Internet connections from multiple available access networks, and serves as a WiFi access point for conventional mobile devices inside the car.

A. System States

As a vehicle drives along, it experiences persistent 3G coverage and sporadic encounters with WiFi access. As illustrated in Fig. 4, we define a stage as the time a vehicle spends between two consecutive WiFi encounters. Each stage comprises of two sub-stages: the period with WiFi coverage from a single access point, followed by the period with 3G-only coverage. We use the subscript $n$ to index a single stage, and characterize
each stage by the following statistics:

- $T_n^w$: duration of WiFi coverage.
- $T_n^g$: duration of the 3G-only sub-stage.
- $B_n^w$: available bandwidth over WiFi when available.
- $B_n^g$: available bandwidth over 3G for the entire stage.

In this work, we assume that a priori knowledge in terms of the distributions for these random variables can either be learned by the vehicle from previous observations, or is directly provided by the infrastructure in the case of managed WiFi service.

Given continuous 3G coverage of the vehicle, it is highly likely that the rate of 3G experienced at one stage is similar to that of the previous one. In addition, according to [10], encounters of WiFi access points tend to cluster together, i.e., short durations of 3G-only periods tend to be followed by short durations of 3G-only periods, and vice versa. This motivates us to model the evolution of $B_n^w$’s and $T_n^w$’s as first-order Markov processes. On the other hand, since WiFi coverage experienced by the vehicle is disconnected over time, we choose to model $B_n^w$’s and $T_n^w$’s as independent random variables, without any correlation over time.

As a shorthand, we denote the system state at the $n$-th stage as $s_n = \{T_n^w, T_n^g, B_n^w, B_n^g\} \in S$, with $S$ representing the entire state space at each stage. Note that since the random variables $T_n^w$’s and $B_n^w$’s are independent over time, observations of their past will not help decision making in the future. Therefore, they are not included as system states.

IV. SYSTEM MODEL

A. Decision Variables

At the $n$-th stage, there are two decision variables involved: choice of interface during the sub-stage with WiFi coverage $W_n$ and choice of interface during the 3G-only sub-stage $G_n$. As indicated below, $W_n$ takes on one out of three alternative values, whereas $G_n$ is a binary variable.

$$W_n = \begin{cases} 
0 & \text{no transmission} \\
1 & \text{use 3G} \\
2 & \text{use WiFi}
\end{cases},
G_n = \begin{cases} 
0 & \text{no transmission} \\
1 & \text{use 3G}
\end{cases}.$$ 

Again, we use the shorthand $a_n = \{W_n, G_n\} \in A$ to denote the action at the $n$-th stage, with $A$ indicating the entire action space. By definitions of $W_n$ and $G_n$, it is straightforward to see that $|A| = 3 \times 2 = 6$.

It can then be derived that the total amount of data transmitted over the 3G and WiFi networks at the $n$-th stage are, respectively:

$$Q_n^w = 1\{W_n = 1\}B_n^wT_n^w + 1\{G_n = 1\}B_n^gT_n^g,$$
$$Q_n^g = 1\{W_n = 2\}B_n^wT_n^w.$$  

In (1) and (2), $1\{\cdot\}$ is the binary indicator function. It equals 1 if the internal statement is true, and 0 vice versa.

B. Reward Functions

In this work, we are concerned with the following aspects as performance metrics of the interface selection policy:

- **monetary cost**: payment incurred for data service over each access network.
- **data delivery efficiency**: total amount of data transferred.

\begin{itemize}
  \item **interface switching overhead**: overhead in terms of disrupted connections or temporary packet drops as a result of switching from one interface to another.
\end{itemize}

Our optimization framework accommodates all three metrics by defining their corresponding reward functions $R_n^w$, $R_n^g$, and $R_n^a$ at each stage $n$, as follows. Note that it is straightforward to extend the framework to accommodate other performance metrics as well.

$$R_n^w(s_n, a_n) = f^{\text{m-w}}(Q_n^w) + f^{\text{m-g}}(Q_n^g),$$  
$$R_n^g(s_n, a_n) = f^{\text{d-g}}(Q_n^g + Q_n^w),$$  
$$R_n^a(s_n, a_{n-1}) = f^{\text{o}}(G_n, W_n, W_{n-1}).$$  

In (3), $Q_n^g$ and $Q_n^w$ represent the amount of data transferred over the 3G and WiFi networks respectively, as calculated in (1) and (2). The monotonically decreasing functions $f^{\text{m-w}}(\cdot)$ and $f^{\text{m-g}}(\cdot)$ reflect pricing schemes over each access network. Similarly, the monotonically increasing function $f^{\text{d-g}}(\cdot)$ indicates the utility of data transfer during the $n$-th stage. Finally, in (5), the monotonically decreasing function $f^{\text{o}}(\cdot)$ represents the severity of system overhead introduced by interface switching.

For the rest of our work, we have chosen the following simple forms for the reward functions:

$$R_n^w(s_n, a_n) = -\kappa^wQ_n^w - \kappa^gQ_n^g,$$
$$R_n^g(s_n, a_n) = \log(Q_n^g + Q_n^w),$$
$$R_n^a(s_n, a_{n-1}) = -1\{G_n \neq W_n\} - 1\{G_n \neq W_{n-1}\}.$$  

Here, the coefficients $\kappa^w > 0$ and $\kappa^g > 0$ correspond to the unit price per data transfer over 3G and WiFi networks, respectively. For notational convenience later on, we also set $R_0^w = 0$ for the first stage $n = 1$.

V. OPTIMAL INTERFACE SWITCHING

A. Optimization Objective

Our system aims at maximizing the expected reward over a finite horizon of $N$ stages:

$$\max_{\{a_n\}_1^N} \mathbb{E} \sum_{n=1}^N R_n(s_n, a_n, a_{n-1})$$
$$= \mathbb{E} \sum_{n=1}^N (\lambda^wR_n^w + \lambda^gR_n^g + \lambda^oR_n^a)$$  

s.t.  
$$1 \leq n \leq N.$$  

In (9), the expectation is taken over all possible realizations of the random variables $T_n^w$’s, $T_n^g$’s, $B_n^w$’s, and $B_n^g$’s. The parameters $\lambda^w$, $\lambda^g$, and $\lambda^o$ signify user-specified relative importance of each performance metric. The goal of the optimization is to choose a set of optimal policies $\{a_n^*\}_1^N = \{G_n, W_n\}_1^N$ to minimize the total expected cost.

Although it is straightforward to evaluate any given policy over a finite horizon, and then to find the optimal policy via exhaustive search, the sheer computational complexity incurred in such an approach is not suitable for practical implementation. We, therefore, present in this section an alternative method based on stochastic dynamic programming (SDP) for finding the optimal policy.

B. SDP-Based Policy

Given observations of past state $s_{n-1}$ and action $a_{n-1}$, we define the maximum expected reward-to-go function at the $n$-th stage as $V_n(s_{n-1}, a_{n-1})$:

$$V_n = \max_{\{a_n\}_1^N} \mathbb{E} \sum_{n' = n}^N R_n'$$
$$= \max_{\{a_n\}_1^N} \mathbb{E}[R_n + \sum_{n' = n+1}^N R_n']$$
$$= \max_{\{a_n\}_1^N} \mathbb{E}[R_n + \max_{\{a_n\}_1^N} \mathbb{E} \sum_{n' = n+1}^N R_n']$$
$$= \max_{a_n} \mathbb{E}[R_n + V_{n+1}(s_n, a_n)].$$  

Fig. 4. Persistent presence of 3G connection and sporadic presence of WiFi connection.
The corresponding optimal policy at stage $n$ is:

$$a^*_n = \arg\min_a E[R_n(s_n, a, a_{n-1}) + V_{n+1}(s_n, a)].$$

(11)

For $n = N$, calculating the maximum terminal reward-to-go $V_N(s_{N-1}, a_{N-1})$ is rather straightforward, as:

$$V_N = \max_{a} E_{s_N|s_{N-1}, a_{N-1}} [R_N(s_N, a, a_{N-1})].$$

(12)

We can then recursively derive values of the maximum reward-to-go functions and corresponding optimal policies for stages $n = N-1, N-2, \ldots, 1$, following (10). Note that for $n = 1$, the value of $V_1$ corresponds to the maximum reward achieved by the optimal policy.

### C. Complexity Analysis

In the SDP policy, the number of state considered at each stage is on the order of $O(|S|\cdot|A|)$, where $|S|$ is size of the state space, and $|A|$ is size of the action space. More specifically, we have chosen to use 10 representative values for each of the random variables $B^w_n$, $B^g_n$, $T^w_n$ and $T^g_n$ in our formulation, leading to a state space of $|S| = 10^4$. As mentioned earlier in IV-A, $|A| = 6$ in this work. The total computational complexity in calculating the SDP policy for $N$ stages is therefore $O(|N|\cdot|A|)$.

In comparison, the amount of computations associated with exhaustive search is on the order of $O(|A|^N\cdot|S|^N)$, since one needs to consider all possible $|A|^N$ policies and evaluate the expected reward of each policy by accounting for all possible system states at each stage. It is obvious that the computational burden of an exhaustive search approach quickly grows prohibitive with as the optimization horizon grows.

### VI. PERFORMANCE EVALUATION

We evaluate our interface switching algorithm using Qualnet 4.5 network simulator [16]. Qualnet is modified to enable interface switching between 3G and WiFi based on a given policy. As illustrated in Fig. 5, a node is traveling at 25 miles-per-hour (mph) along a road of 2000 meters. 3G coverage is available for the entire length of the road. Three WiFi access points (APs) are placed across the street such that WiFi coverage is only available within the range of each AP. For a given policy, we vary the background 3G and WiFi CBR traffic and APs placement based on Gaussian distributions. With CBR background traffic, TCP application traffic are sent from the mobile node equipped with the switching policy. A file transfer session is activated at the beginning of the simulation, and keeps track of packet delivery over both interfaces. At the end of the simulation, packet-level log file allows us to parse the amount of data transfer over each interface, and calculate the associated monetary costs over the 3G network. Table I summarizes the parameters used for the evaluation.

While our optimization framework is general enough to accommodate a wide range of statistical models, we have chosen a concrete example for simulation evaluations. Based on [10], evolutions of both available bandwidth and duration over 3G ($B^g_n$’s and $T^g_n$’s) are modeled as first-order Gauss-Markov processes. Bandwidth and duration over WiFi ($B^w_n$’s and $T^w_n$’s) are modeled as independent random variables following Gaussian and exponential distributions, respectively.

Given three WiFi coverage areas in the simulation, it is easy to see that there are all together $(2 \times 3)^3 - 1 = 215$ valid interface switching policies, after discounting the option of no transmission throughout the simulation. Figure 6 presents the tradeoff in monetary cost, data transfer efficiency, and interface switching overhead rewards as achieved by all these policies. It can be noted that they span a wide range in the 3D tradeoff space. Note that policies lying on the paraeto surface in this graph represent the optimal choices for certain relative weighting factors between the three reward terms.

In our simulation evaluation, we have chosen $\kappa^w = 0$ to reflect the fact that today’s WiFi access services tend to be free in public areas.

<table>
<thead>
<tr>
<th>Parameter</th>
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</tr>
</tbody>
</table>

TABLE I
SIMULATION PARAMETERS

Note that in (10), the expectation is taken over $s_n, a_{n-1}, T^w_n$, and $B^w_n$. For $n = N$, calculating the maximum terminal reward-to-go $V_N(s_{N-1}, a_{N-1})$ is rather straightforward, as:

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In our simulation evaluation, we have chosen $\kappa^w = 0$ to reflect the fact that today’s WiFi access services tend to be free in public areas.
and $\lambda$ and WiFi-only based policies attains an overhead reward of $-\lambda$ within the entire policy space. It is also interesting to note that no SDP-based policies successfully attain the optimal tradeoff between the two reward terms without the need of exhaustive search expected, the SDP-based policies successfully attain the optimal tradeoff among all policies with the same overhead.

As confirmed by simulation studies, the proposed SDP-based policy can strive the best tradeoff over a wide range of user preference choices, with moderate computation complexity suitable for practical implementations. For future work, we plan to investigate the scenario of more than two available access networks, as well as extending the current optimization framework for multiple competing application traffic flows.

VII. CONCLUSIONS AND FUTURE WORK

In this paper, we present an optimization framework for interface switching among multiple heterogeneous networks in vehicular communications. Our problem formulation allows for flexible tuning of user-specified preferences among various performance metrics, such as monetary cost, data transfer efficiency, and interface switching overhead. As confirmed by simulation studies, the proposed SDP-based policy can outperform the best tradeoff over a wide range of user preference choices, with moderate computation complexity suitable for practical implementations. For future work, we plan to investigate the scenario of more than two available access networks, as well as extending the current optimization framework for multiple competing application traffic flows.

REFERENCES


Figure 8 shows the comparison between the four schemes, when varying one of the weighting parameters and keeping the other two constant. It can be noted that the SDP-based policy consistently outperforms the heuristic schemes for all combinations of weighting factors. This, again, confirms optimality of the proposed scheme.

In Fig. 7, each subgraph shows the tradeoff between performance and monetary rewards among all policies with the same overhead. In addition, the red circles indicate policies calculated by the proposed SDP algorithm with various choices of the relative weights $\lambda^d$, $\lambda^m$, and $\lambda^o$. As expected, the SDP-based policies successfully attain the optimal tradeoff between the two reward terms without the need of exhaustive search within the entire policy space. It is also interesting to note that no SDP-based policies attain an overhead reward of $-2$ or $-4$ (corresponding to twice and four times of interface switching), as these policies tend to be outperformed by alternatives with overhead reward of $-1$ or $-3$, respectively.

We also compare the proposed SDP-based policy against a few heuristic schemes, as follows:

- **Always Switching**: use 3G network as a default option, and switch to WiFi whenever its presence is encountered.
- **WiFi-only**: stay on WiFi regardless of observed WiFi presence information.
- **3G-only**: stay on 3G regardless of observed WiFi presence information.

Our performance metric is the overall reward function as calculated in (9), over various choices of the relative weighting factors $\lambda^d$, $\lambda^m$, and $\lambda^o$.