

Geo-intelligent Traffic Scheduling For Multi-Homed On-Board Networks

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ABSTRACT

In vehicular mobile communication environments, unpredictable network performance along the route of a cruising vehicle imposes significant difficulties for many applications to maintain the required quality of service. To address this issue, we present the concept of geo-intelligence, which reduces bandwidth uncertainty by exploiting the correlation between location and wireless network performance. Geo-profiles are used to characterize network parameters as a function of geographic location. These profiles are then used to predict the expected network performance at each location along the route. As a concrete example, we present the design of a geo-intelligent traffic scheduler for scheduling downlink user traffic among multiple wireless access links in a multi-homed onboard network. Our simulations, which are based on mobile bandwidth traces collected from real-world experiments, reveal that geo-intelligence can significantly reduce packet loss experienced by multimedia applications.

Categories and Subject Descriptors

C.2.1 [Network Architecture and Design]: Wireless communication

General Terms

Experimentation, Measurement, Performance

Keywords

Geo-intelligence, Traffic Scheduling, Bandwidth Predictability, Mobile Computing

1. INTRODUCTION

It is widely known that the bandwidth of Wireless Wide Area Network (WWAN), e.g., HSDPA, 3G, and WiMaX, fluctuates over time and space. These variations can be attributed to a variety of factors including network load, operator scheduling decisions, presence of tall structures that block line-of-sight, etc. In the context of high-speed vehicular mobility, our earlier work [1] has demonstrated that the uncertainty associated with WWAN bandwidth reduces

significantly when observations from past trips are used to predict bandwidth. In particular, our analysis revealed that WWAN bandwidth is significantly more predictable when location is used as a context. In this paper, we propose a novel principle called *geo-intelligence*, which seeks to exploit this strong correlation between location and WWAN link behavior in a high-speed vehicular mobility scenario.

The main idea behind geo-intelligence is to characterize wireless network performance, e.g., available bandwidth, as a function of geographical location by conducting repeated measurements at different locations. The measurement samples are then analyzed to create a statistical profile of the WWAN for each individual location, which we refer to as a *geo-profile*. The geo-profile captures the coupling between WWAN performance and location and hence can be used to predict the network behavior as a function of location. Geo-intelligence, i.e., the ability to estimate WWAN link performance at each location along a route in a fast moving environment can be useful in several aspects of mobile communication, e.g., admission control, congestion control, and adaptive rate control.

In this paper, we put the principle of geo-intelligence to practice in the context of on-board communication networks and demonstrate the significant performance improvement that can be achieved. In a typical on-board communication network as illustrated in Fig. 1(a), a Mobile Router (MR) seamlessly connects multiple user devices inside the vehicle to the Internet. The user devices are simply plugged in to an on-board LAN (wireless/wired) and the MR connects this LAN to the Internet using one or more WWAN links. The MR in conjunction with a Home Agent (HA), transparently manages the mobility of all on-board devices using the NEMO basic protocol [2]. Recently, several such commercial systems (e.g., iComera¹, 21net², wifirail³) have been deployed for providing Internet services in public transport vehicles.

The MR is usually *multi-homed*, i.e., the MR maintains parallel WWAN links. Prior works [3, 4] have substantiated that multi-homing can improve the system capacity and reliability by leveraging provider and technology diversity. Under normal operating conditions, a large number of user flows are active at any given time in an on-board network. The HA in conjunction with the MR is responsible for assigning individual flows to one of the WWAN links. It is desirable that the flow scheduler effectively utilizes the

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¹<http://www.iComera.com>

²<http://www.21net.com>

³<http://www.wifinet.com>

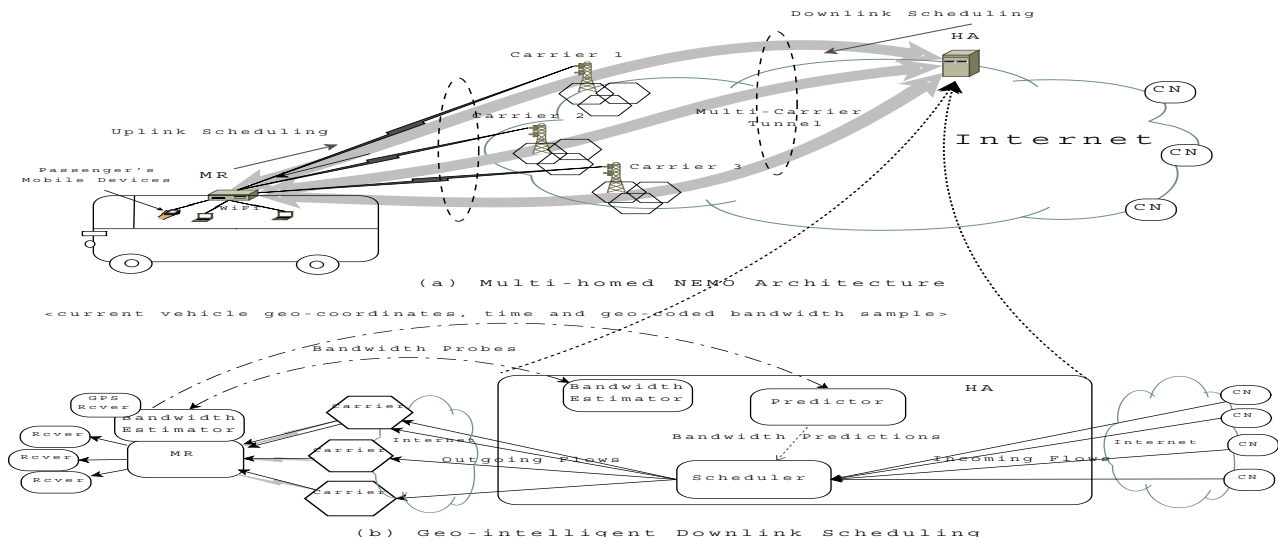


Figure 1: Design of the geo-intelligent traffic scheduler

aggregate capacity of all WWAN links. Assigning too many flows to one particular link can overload the link resulting in congestion, packet loss and increased delay. On the other hand, underutilization of a link leads to inefficient usage of expensive resources. To avoid these problems, the scheduler must ideally have *a priori* knowledge of the capacity of each WWAN link. This is particularly challenging in a high-speed mobility scenario, since the capacity of WWAN links can fluctuate significantly as the vehicle travels along its route.

In this paper, we demonstrate how the principle of geo-intelligence can be applied to address the aforementioned problem by designing and testing a geo-intelligent traffic scheduler for a multi-homed on-board network. Prior research in resource scheduling for multi-homed systems [5–7] has primarily focused on static networks, where the location of the multi-homed network does not change. To the best of our knowledge, this is the first attempt at addressing this issue in the context of high-speed vehicular mobility. We also present results from simulations using empirical WWAN bandwidth traces collected during an extensive measurement campaign consisting of 75 repeated trips along a 7Km route in the Sydney metropolitan area. The simulations demonstrate that by employing geo-intelligence in the traffic scheduler, packet loss experienced by multimedia flows reduces by upto 90% as compared to the plain vanilla approach which does not use geo-intelligence. We believe that the encouraging results from this first attempt at instantiating the concept of geo-intelligence will open up many other interesting and exciting applications in high-speed mobile computing.

The rest of the paper is organized as follows. We present the design of the geo-intelligent scheduler in Section 2. In Section 3, we summarize the measurement campaign conducted for collecting the mobile bandwidth traces. Simulation results are presented in Section 4. Finally, Section 5 concludes with a discussion on future research directions.

2. GEO-INTELLIGENT SCHEDULING

In this section, we present a detailed overview of the proposed geo-intelligent traffic scheduler. We focus on the downlink traffic, given that it makes up the bulk of the traffic in a typical on-board network. According to the NEMO ba-

sic protocol, all inbound traffic is routed through the HA as illustrated in Fig. 1(a). As such, the downlink scheduler is housed at the HA. Using the same concepts described herein, one can readily develop a geo-intelligent uplink scheduler, housed at the MR.

To demonstrate our idea, we have chosen to use the proportional fair scheduling discipline [3, 8, 9] and incorporate geo-intelligence. However, the same design philosophy can be used in conjunction with any other scheduler. In a proportional fair scheduler, the traffic assigned to each link is in proportion to the available bandwidth of the corresponding end-to-end path, which in the context of an on-board network is the path between the HA and MR. It is well documented that the last hop WWAN link forms the bottleneck along the end-to-end path between the HA and MR. Hence, the available bandwidth on the WWAN link is representative of the bandwidth corresponding end-to-end path. Assuming that the total traffic load in the system is λ , the flows assigned to link i by the proportional fair scheduler would be such that the traffic load on link i , λ_i , is given by

$$\lambda_i = \frac{\hat{\mu}_i}{\sum_i \hat{\mu}_i} \times \lambda \quad (1)$$

where $\hat{\mu}_i$ represents the estimated available bandwidth of link i . However, the bandwidth of the WWAN links vary significantly, as the vehicle cruises along its route. Hence, in order to make a correct scheduling decision it is important the scheduler can accurately estimate the available bandwidth as the vehicle rapidly changes its location. To address this issue, we propose to incorporate *geo-intelligence* into the traffic scheduler. Geo-intelligence seeks to reduce the bandwidth uncertainty by exploiting recent findings [1], which demonstrate the strong correlation between WWAN link behavior and geographical location in a high-speed vehicular mobility scenario. The main idea is to develop a characterization of each WWAN link behavior as a function of the geographical location by conducting empirical measurements. The resulting *geo-profiles* are used to estimate the expected network performance, e.g., available bandwidth, at each location along the route.

In the context of the traffic scheduler, we focus on the geo-profiles of the available bandwidth for the WWAN links. For

creating the geo-profiles, we deploy an on-line bandwidth estimation algorithm at the HA and MR. A number of algorithms that rely on either active or passive probing [10] have been proposed. Any program that can converge to an estimate quickly would be a suitable candidate, given the high speed mobility of the on-board network. We have used a simple lightweight estimation algorithm in Section 3 for collecting empirical bandwidth traces, which can be a suitable candidate. The location of the vehicle is recorded by installing a GPS receiver at the MR. As shown in Fig. 1(b), the probed bandwidth samples are tagged with the location coordinates and time and stored at the HA. Depending on the granularity used to represent each location, the bandwidth samples that are contained within the same location are averaged to represent the estimated available bandwidth for that location. The geo-profile for each location is stored as a probability distribution function (PDF) or a raw collection of samples. The profiles are continuously updated on-the-fly as the vehicle makes new trips. Given that WWAN operators upgrade their equipment frequently in an effort to improve network performance, the old samples can be aged to ensure that the geo-profiles are an accurate representation of the current network conditions.

The geo-profiles are used to predict the available bandwidth at each location along the route. The MR periodically reports its current location to the HA. The HA then uses the corresponding geo-profile for the WWAN links to predict the available bandwidth at this location. Several well-established prediction algorithms ranging from simple order-0 to higher order stochastic models [11–14] can be employed for bandwidth prediction. Equation 1, which governs the scheduling operation can now be updated as follows. Let $\hat{\mu}_i^l$, denote the estimated bandwidth for the WWAN link i at location l . The proportional scheduler then allocates flows to the links such that the total traffic allocated to link i , is given by,

$$\lambda_i = \frac{\hat{\mu}_i^l}{\sum_i \hat{\mu}_i^l} \times \lambda \quad (2)$$

The flow scheduling operation is triggered when the HA is informed about the change in the location of the on-board network. The predictor provides the geo-intelligent scheduler with the updated predictions of the link bandwidths for the current location, and the scheduler executes Equation 2 to reschedule flows. The rescheduling is also triggered in the event that a new flow enters the system or when an existing flow departs.

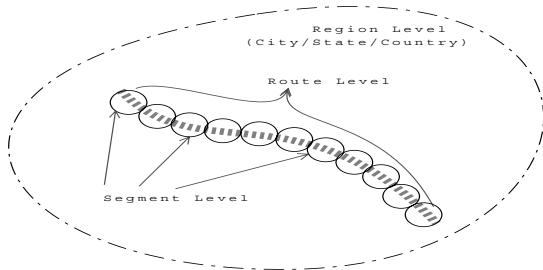


Figure 2: An illustration of different granularities for representing location

The granularity used to represent the geographical location is an important system parameter and has implications on

the performance of the geo-intelligent scheduler. Figure 2 illustrates a range of possibilities. If one employs coarse granularity, an entire geographical region such as a suburb would correspond to a location segment. We refer to this representation as *region-level*. On the other hand, one could use an extremely fine grained representation, *segment-level*, wherein a small section of the road (e.g., 500m section) corresponds to a location segment. In between these two extremes, is the granularity of a route, i.e. a sequence of road segments, referred to as the *route-level* representation. In our simulations presented in Section 4, we evaluate the impact of using different location granularities on the performance of the geo-intelligent scheduler.

3. MEASUREMENT CAMPAIGN

In this section, we briefly describe our empirical measurement campaign for collecting WWAN bandwidth traces in a high-speed vehicular environment. We have used these traces in Section 4 to demonstrate the effectiveness of our proposed scheduler using simulation-based evaluations. We present details of the software and hardware components and describe the field trips.

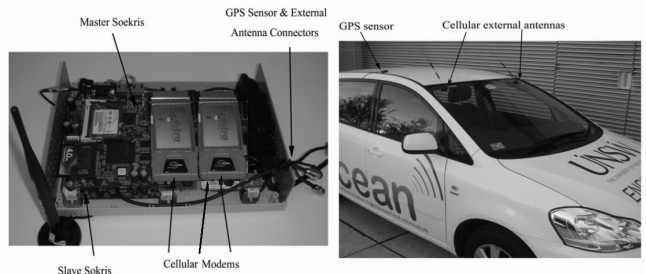


Figure 3: Measurement setup

We developed a simple client-server measurement system, with the server deployed at the University of New South Wales (UNSW) on a standard RedHat Linux machine. The client was installed in a vehicle, and comprises of two Soekris Net4521 boards (133Mhz processor and 16MB memory), which are interconnected via 10Mbps Ethernet and configured to operate in the master and slave mode (see Figure 3). A total of three PCMCIA cellular modems are housed in the system, with two modems connected to the master board and one to the slave board. To account for network and technology diversity, we selected three WWAN providers with two providers (A and B) offering HSDPA [15] services with different specifications and the third provider (C) supporting a pre-WiMaX proprietary standard, iBurst [16]. The advertised peak rates for A, B and C are 7.2Mbps, 3.6Mbps and 1Mbps respectively. The boards are enclosed in a protective casing and housed in the boot of the OCEAN⁴ vehicle. To enhance the wireless signal reception, the modems are connected to external antennas, which are mounted on the car windshield. A Garmin GPS18 GPS sensor is installed on the top of the vehicle and is connected to the master board for recording the vehicle location.

We conducted an eight-month bandwidth measurement campaign to collect the bandwidth traces. We selected a 7KM route, which originated at UNSW and terminated in Sydney CBD. Figure 4 depicts the trajectory of the route. Note that, the chosen route is a fairly typical representa-

⁴OCEAN (On-board Communication Entertainment And information) is a vehicular Internet project at UNSW.

tion of daily commute for a person who lives near UNSW and drives to work in Sydney CBD everyday. In the eight month period, we conducted 75 repeated trips each along this route. The trips were randomly conducted during normal commuting hours including morning/evening rush hours and off-peak periods.



Figure 4: Route trajectory

We concentrated on measuring the downlink bandwidth and implemented a simple and lightweight packet-train based client server program, which was simultaneously run over each WWAN link. We refer the reader to [1] for further details on the measurement program and validation results. We did not use continuous measurements, e.g., bandwidth saturation test, to avoid generating large amount of network traffic on the bandwidth expensive WWAN links. In our measurements, we controlled the sampling interval (T) by using the vehicle velocity (V , collected from the GPS sensor) and geographical sampling granularity (e.g., $D = 200m$), e.g., $T = D/V$. Thus we have collected one bandwidth sample for approximately every 200m section of the route. Note that, the data samples collected over one trip represent a space-ordered sequence (i.e. ordered by locations along the route). Occasionally, the probes used for estimating the bandwidth were lost, leading to a few missing samples. To deal with this occasional loss, we use 500m road segments as the smallest resolution for representing location. The average value of the samples collected over each segment is used to represent the bandwidth for that segment.

4. SIMULATION

In this section, we will present the results from our trace-driven simulations. We demonstrate the performance improvement achieved by employing geo-intelligence in the traffic scheduler in an on-board network as compared to not making use of any location-specific knowledge. We also investigate the impact of different location granularities on the performance of the geo-intelligent traffic scheduler.

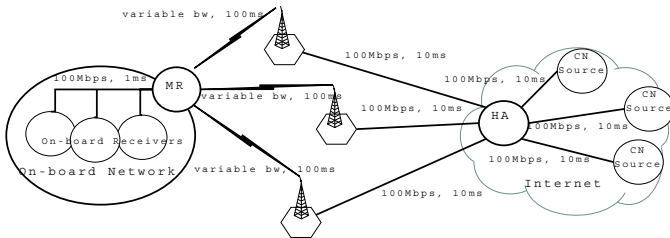


Figure 5: Simulation Setup

4.1 Simulation Setup

The simulations were conducted using the popular *ns-2* simulator. We have simulated an on-board NEMO network

as illustrated in Figure 5. The MR maintains three parallel WWAN connections, which correspond to providers A, B and C from our empirical measurements in Section 3. The bandwidth of the WWAN links is varied by playing back the corresponding trace file for the 3 providers form one particular trip. This allows us to simulate the mobility of the on-board network along the 7Km route discussed in Section 3. We assume that the propagation delay along each WWAN interface is 100ms. Since most wired links in the Internet have sufficiently high capacity and small delays as compared to the last-hop WWAN links, we assume those links have a capacity of 100Mbps with a small propagation delay of 10ms. We assume the on-board network is a 100Mbps LAN with an 1ms propagation delay. We assume that the queue size at each cellular tower is 50 packets.

As in Section 2, we only consider downlink traffic. We have simulated a scenario, wherein several on-board users are downloading streaming audio files from certain Internet servers, which are referred to as Corresponding Nodes (CN). We assume 64Kbps constant bit rate (CBR) flows with a fixed packet size of 180bytes, which correspond to G771 encoded audio streams. Note that, according to the NEMO basic protocol, all flows are routed via the HA to the on-board network. Flow arrival follows the Poisson distribution, with a variable mean λ and the duration of each flow is exponentially distributed with mean, $\beta = 180seconds$. The proportional fair flow scheduler (discussed in Section 2) is implemented in the HA by using the ns-2 hash classifier. Note that, as we focus on analyzing the performance of the non-elastic multimedia flows in this paper, the flow rates are all constant (64Kbps). Thus the flow scheduling decision can be made by simply replacing the volume of the traffic in Equation 2 by the number of the flows. We also assume that the HA always has the knowledge of the vehicle location.

In our simulations, we use the simple order-0 exponential weighted moving average (EWMA) predictor as a example for estimating the WWAN link bandwidths from the geo-profiles. The geo-intelligent EWMA predictor is expressed as:

$$\hat{\mu}_i^l = \alpha \times BW_i^l + (1 - \alpha) \times \hat{\mu}_i^l \quad (3)$$

, where $\hat{\mu}_i^l$ is the EWMA mean bandwidth of WWAN link i at location l , BW_i^l is the new bandwidth sample of WWAN link i collected at location l , and α is the smoothing factor used to phase out the stale samples. Based on our experiments, we have found the prediction is more accurate with EWMA when the smoothing factor, α is set to 0.125. Also the prediction error becomes smaller when the geo-profile for training contains at least 35 trips of data. Thus, we split the bandwidth traces from our 75 trips into two halves. The first 35 trips are exclusively used to create the geo-profiles and train the EWMA bandwidth predictor for each WWAN link. The second half consisting of 40 trips is used for evaluating the performance of the geo-traffic scheduler. We use the packet loss rate as the performance metric in this paper. We simulate each trip by varying the bandwidth of the three WWAN links in accordance with the corresponding traces for the trip. 40 repeated trips are simulated and the results presented are averaged over the 40 runs achieving over 85% confidence level for less than 5% relative precision. We assume that the on-line bandwidth predictor is operational during each of these trips. Consequently, the

EWMA predictor update its bandwidth predictions as each trip progresses.

We compare the performance of the geo-intelligent scheduler to two schemes, which do not employ geo-intelligence. The first one is the simple round-robin (RR) flow scheduler, which simply cycles through all the links and transmits one flow on each link. The second scheme is a simple proportional scheduler, which uses the provider advertised bandwidth statistics to estimate the bandwidth of each WWAN link. As such, we refer to this scheduler as Adv (i.e., Advertised). It should be noted that these estimates are computed *a priori* based on data available from the providers and are assumed to be location invariant. Most WWAN providers represent the expected downlink capacity for their network as a broad range. For example, Provider A, B and C advertise a range of 1500-3000 Kbps, 600-1400 Kbps and 0-1000 Kbps, respectively. For the Adv scheme, we use the mean value of this range as the estimated capacity of each link, i.e., 2250 Kbps, 1000 Kbps and 500 Kbps for providers A, B and C, respectively.

We simulate three versions of the proposed geo-intelligent traffic scheduler, each using a different location granularity: region-level, route-level and segment-level, as discussed in Section 2. To generate the geo-profile for the region-level, we used the measurement apparatus from Section 3 and conducted several empirical experiments to collect bandwidth samples over the entire Sydney metropolitan area. The route used in our simulations is entirely encompassed in this region. For the route-level, we assume that the entire 7KM route corresponds to location segment. For the segment mean, we assume that a 500m section of the road corresponds to a location segment. As a benchmark, we also include a version of the geo-intelligent scheduler, Optimal (Opt), which has perfect knowledge of the bandwidth of all links and hence achieves the best possible performance.

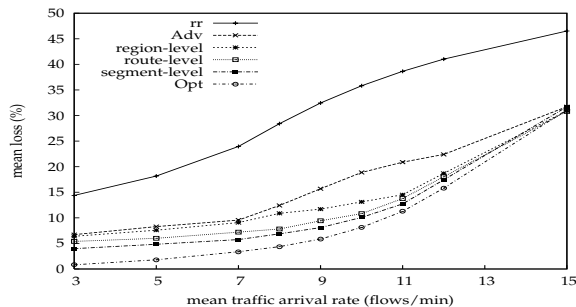


Figure 6: Loss Rate as a function of traffic load

4.2 Impact of Network Traffic Load

Figure 6 plots the average value of the loss rate experienced over the entire route as a function of the traffic load, λ , for the different scheduling schemes. The Opt scheme illustrates the best achievable performance. As expected RR achieves poor results, since the scheduler tries to distribute the packets equally across all interfaces, independent of the available bandwidth of the links, thus leading to significant packet loss when certain links are overloaded. Even the Adv scheme performs significantly better with more than 50% reduction in the packet loss as compared to RR. However, all geo-intelligent schedulers perform substantially better than the Adv scheme. In particular, we focus on the part of the graph where the traffic load varies from 7 to 12 flows/minute,

which corresponds to the normal operational range of the on-board network. The region to the left denotes a lightly loaded network and the region to the right corresponds to the overloaded case. Since, the segment-level relies on fine-grained statistics, it can adapt quickly to changes in the link behavior, thus achieving performance similar to the Opt scheme. Segment-level results in a reduction in the loss rate by about 5-20% and 10-30% compared with the coarse-grained route-level and region-level schemes, respectively. Note that, when the network is heavily loaded, i.e., when $\lambda > 12$, all schemes (excluding RR) expectedly achieve similar high loss rates, due to the fact that the total incident traffic consistently exceeds the system capacity.

In the rest of the simulations we will focus on the results for the case when the traffic load, λ is 10 *flows/min*, which represents the state when the load on the system is close to saturation on average.

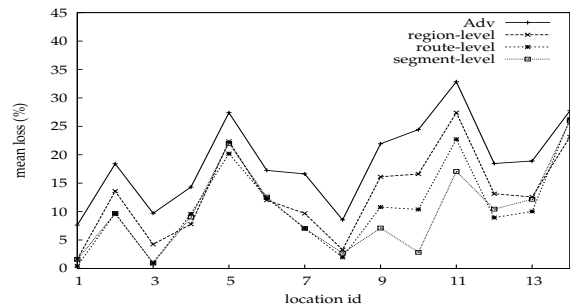


Figure 7: Mean packet loss at individual segments along the route

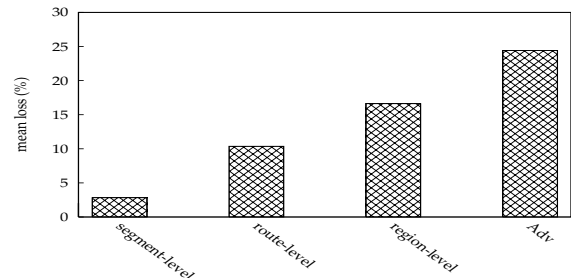


Figure 8: Mean Loss rate at segment #10

4.3 Loss Rates at Location Segments

In Fig. 6, we presented results averaged over the entire trip. We now concentrate on the individual location segments along the route, in an effort to investigate if interesting patterns emerge. We use a granularity of 500m for each location segment. We do not include RR in this comparison due to its poor performance, as observed from Figure 6. The segments are labelled by ids. Figure 7 represents the average value of the loss rate at each individual segment over the 40 trips. Observe that for all locations, the Adv scheme consistently performs worse than all the geo-intelligent schedulers. For example, at segments 9-11, the segment-level reduces the packet loss by over two folds as compared to Adv. At certain locations, e.g., location #4 and #8, the schemes with different granularities all exhibit similar performance. However, at other locations, significant disparities emerge amongst these schemes. For example, at segment #10, segment-level outperforms route-level and region-level by a factor of 4 and 6, respectively. Fig 8

highlights the difference in the performance of the different schedulers at segment #10. These results, imply that using finer-grained statistics can significantly improve the performance of the scheduler at certain locations, since they allow the scheduler to adapt quickly to changes in the link capacities. Coarse-grained schemes aggregate the statistics over a larger region and thus, are unable to accurately predict instantaneous fluctuations and subsequently react to these events.

5. CONCLUSION AND FUTURE WORK

In this paper, we have presented the *geo-intelligence* concept as a solution for dealing with the significant bandwidth variations inherent in high-speed vehicular mobile communication environment. Geo-intelligence exploits the strong correlation between location and WWAN network performance. Geo-profiles are used to characterize the network parameters as a function of geographic location. These profiles are then be used to predict the expected network performance at each location along the route. As a concrete example, we have presented the design and implementation of a geo-intelligent traffic scheduler for scheduling downlink user traffic amongst multiple WWAN links in a multi-homed on-board network. Our simulations, which are based on mobile bandwidth traces collected from real-world experiments, revealed that geo-intelligence can significantly reduce packet loss experienced by multimedia flows.

Although our preliminary results are certainly encouraging, we have not explored the bounds of performance improvements that could be achieved with geo-intelligence. For example, we have used the simple EWMA algorithm for estimating the bandwidth. There is opportunity to explore more sophisticated prediction algorithms which use higher order stochastic models such as Fixed Order-N Markovian, Variable Mixed Order-N Markovian (e.g., PPM [13], Lezi [14]), etc., and evaluate the optimal number of samples required to train these models. While our implementation was based on the proportional fair scheduling principle, it would be interesting to evaluate whether and how much other scheduling strategies, such as utility fairness, would benefit from using geo-intelligence. It should be noted that our experiments were confined to a small part of a city. More comprehensive experiments using many different routes through more diverse terrains (e.g., along freeways, mountains, tunnels, industrial areas, etc.), preferably in different parts of the world, would enable us to make more generalized conclusions about the benefits of geo-intelligence. Finally, it would be an interesting exercise to implement a prototype of a geo-intelligent scheduler and evaluate its performance in a real-world setting.

With successful testing in the context of mobile multi-homing, geo-intelligence has the potential to open up a new direction of research in mobile computing. The ability to predict wireless link behavior at future locations can be harnessed to design a new set of ge-intelligent networking algorithms and protocols in high-speed mobile communication environment. Although we exclusively focused our experiments on voice over IP flows, performance evaluation of other multimedia applications, or even elastic data applications will constitute a useful future research direction.

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