Network-Aware Applications in Wireless Networks

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***Abstract*—Wireless network can experience highly variable network performance. Hence, Building services in wireless networks is challenging due to the rapidly changing operating contexts, which often lead to situations where application adaptation is required. If an application does not adapt its network communication to these changes, they can interfere with the performance seen by the user. This paper describes two examples of application adaptation in two different wireless network environments.**

I. INTRODUCTION

Wireless networks present unusual challenges since they are characterized by unpredictable connectivity and widely-varying bandwidth. A wireless node can experience rapid and large-scale changes in bandwidth availability. If an application that is running on such node does not adapt its network communication to these changes, they can interfere with the performance seen by the user. Therefore, supporting wireless applications requires coping with the a typical patterns of connectivity that characterize them.

Network-aware applications are such applications that attempt to adjust its resource demands in response to network performance variations. Usually, network-aware applications dynamically adjust their demand of network resources (e.g., bandwidth) to the availability of the resources. According to Bolligers description [2] and other related research, Network-aware applications have two basic aspects: they must have the ability to monitor or get information from network monitors about the current status of the underlying network (network awareness), and be able to adjust their behavior based on the collected information (network adaptation).

This paper describes two examples to application adaptation in two different wireless environments: vehicular networks and enterprise wireless networks.

II. APPLICATION ADAPTATION IN VEHICULAR NETWORKS

In the near future, the number of vehicles equipped with computing technologies and wireless communication devices is poised to increase dramatically. Various novel applications that make use of vehicular networks have been proposed, ranging from traffic management and urban sensing to multimedia sharing.

Rate adaptation is a critical component to ensure optimal system performance in these dynamic mobile environments. The IEEE 802.11 protocol specifications allow multiple transmission rates at the physical layer (PHY), which use different modulation and coding schemes. Higher data rates allow high quality links to transmit more data, but have a higher loss probability on low quality links. On the other hand, a low data rate is more resilient to low quality links, but fails to achieve a high throughput in a high quality link. Rate Adaptation is the problem of selecting the best transmission rate based on the real-time link quality, so as to obtain maximum throughput at all times.

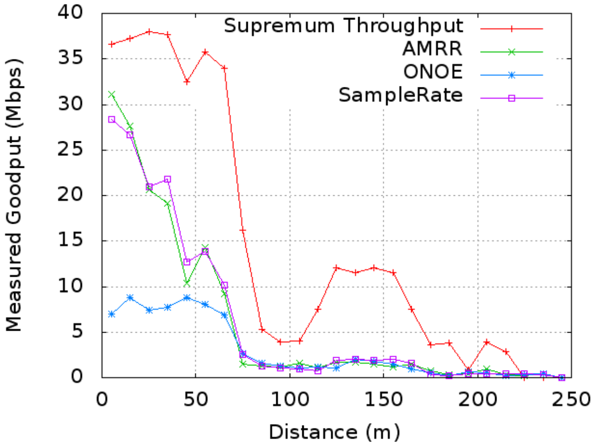

Fig. 1. Measured goodput averaged over distance for different state-of-the-art rate adaptation algorithms compared against the supremum goodput.

Several rate adaptation algorithms ([6], [9], [4], [7], [1], [13]) have been proposed in the literature. However, all the existing work in rate adaptation is based on traditional indoor wireless networks. Vehicular networks have vastly different characteristics from indoor wireless networks, as the link conditions in these networks change more rapidly due to the high mobility of the nodes. Rate adaptation in vehicular networks faces the following key challenges: (1) due to the rapid variations of the link quality caused by fading and mobility at vehicular speeds, the transmission rate must adapt fast in order to be effective, (2) during infrequent and bursty transmission, the rate adaptation scheme must be able to estimate the link quality with few or no packets transmitted in the estimation window, (3) the rate adaptation scheme must distinguish losses due to environment from those due to hidden-station induced collision.

We performed a series of outdoor experiment in order to understand the problems encountered by rate adaptation in vehicular networks. The experiments are conducted in a campus parking lot setting, where we measure average goodput received by a vehicular client at different distances using different current state-of-the-art rate adaptation schemes. Figure 1 plots the average goodput achieved by three current state-of-the-art rate adaptation schemes, AMRR, ONOE, and SampleRate. In order to provide a benchmark for comparison, we compute from our earlier experiment with fixed bitrates, the maximum goodput possible at each distance range, which we term the Supremum Throughput for each distance bin. The figure shows that there is a significant underutilization of link capacity, which deteriorates link goodput in vehicular clients. These results show that there are some important challenges faced by rate adaptation algorithms in vehicular environments,

We designed, implemented and evaluated CARS[1] [10], a novel Context-Aware Rate Selection algorithm that makes use of context information (e.g. vehicle speed and distance from neighbor) in addition to the frame transmission statistics received from the lower layers to systematically address the above challenges, while maximizing the link throughput. The context information used in CARS broadly consists of information about the environment that is available to the node and which has an effect on the packet delivery probability. Such information could include the position, speed and acceleration of the vehicle, the distance from the neighboring vehicle, and environment factors such as location, time of day, weather, type of road and traffic density.

As a starting point, we choose the two most significant of these parameters:distance from the receiver and the vehicles speed. In our work [10], we developed CARS algorithm assuming the use of distance and speed context information. The key idea of the CARS algorithm is to estimate the link quality using both context information as well as past history. The CARS rate selection algorithm estimates the packet error by means of a weighted decision function involving two functions. The first function uses the empirical model we built that accepts the context information, transmission rate and packet length as input parameters, and outputs the estimated packet error rate. We choose to derive a simple empirical model for delivery probability using measurements from real outdoor vehicular experiments. This is because we wanted to show that model based schemes can improve rate adaptation, even with a simple model. Measurements from extensive outdoor vehicular experiments were used to build this empirical model, in which we vary the distance between the vehicles, the speed, the packet size and the bitrate. The second function uses an exponentially weighted moving average (EWMA) of past frame transmission statistics for each bitrate, similar to schemes such as SampleRate [1].

We implemented the CARS algorithm on the open-source MadWifi wireless driver for Atheros chipset wireless cards. The implementation consisted of 520 lines of C code. Context information required for CARS was obtained using GPSDaemon, a VANET application that interfaced with the wireless driver using a generic /proc interface. Any other VANET application can be extended to use this same interface, so CARS can be deployed with no change to the 802.11 protocol or to the hardware.

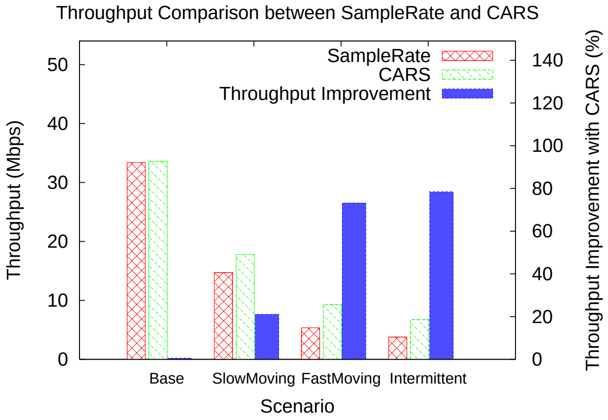

Fig. 2. Histogram showing the comparison of throughput achieved by CARS and SampleRate in different scenarios

Figure 2 shows the comparison of throughput between CARS and SampleRate for 5 minute experiments in four different mobility scenarios: 1) Base: the two cars are stationary next to each other, 2) SlowMoving: the two cars are moving around our campus following each other at 25mph speed, 3) FastMoving: the two cars are moving on an interstate highway following each other in high car/truck traffic conditions at 70mph speed, 4) Intermittent: A more stressful intermittent connectivity scenario where cars are mostly out of range and periodically meet each other. In the Base scenario, both CARS and SampleRate give the same throughput. In all the other scenarios, CARS gives significantly better throughput, and the more stressful the condition in terms of varying distance and speed, the more is the throughput gain. In the SlowMoving, FastMoving and Intermittent scenarios, the throughput improvement is 21%, 73% and 79% respectively. The reason CARS performs better in the stressful scenarios is because it adapts the bitrate faster as the conditions change.

III. APPLICATION ADAPTATION IN ENTERPRISE WIRELESS NETWORKS

Power control mechanisms in wireless networks have been used to meet two different objectives to reduce energy consumption in mobile devices, so as to conserve battery life, and to reduce interference in the shared medium, thereby allowing greater re-use and concurrency of communication. Recent theoretical work has shown that ideal medium access protocol using optimal power control can improve channel utilization by up to a factor of $\sqrt{\rho}$, where ρ is the density of nodes in the region (using fluid model approximations) [3]. Power control mechanisms [5], [11], [14] typically try to optimize the floor space acquired by wireless transmissions by limiting the transmit power of control and data packets, thereby providing opportunity for multiple flows to coexist.

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[1] This work was done in collaboration with DiscoLab in Rytgers University (http://discolab.rutgers.edu/)

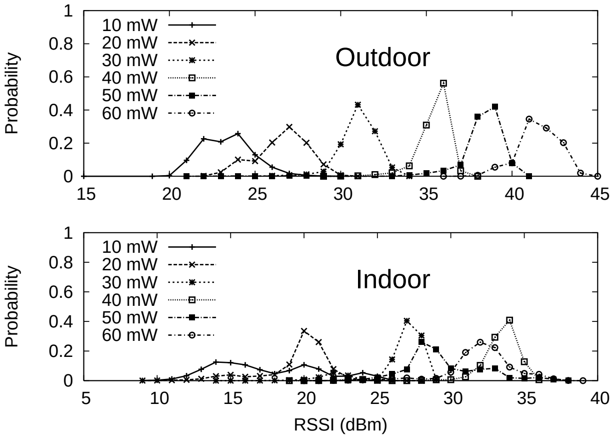

Fig. 3. **Probability Distribution of RSSI for varying power levels at the transmitter is shown in the figure. The top figure corresponds to outdoor scenario with 6 distinguishable power levels while bottom figure shows the effect of increased multipath and interference in the indoor WLAN scenario with the number of distinct power levels reduced from 6 to 3. Band:802.11g Data Packet Size:1Kbytes**

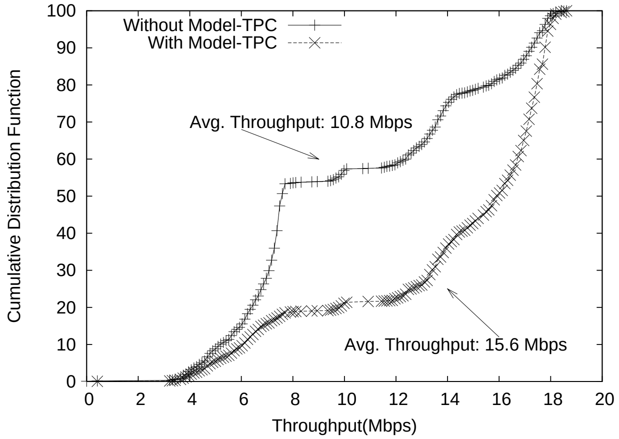

Fig. 4. Cumulative distribution of throughput achieved by the wireless clients with/without the empirical model for adaptation at location T1. The average throughput for the adaptation process is also shown in the figure

Conventional power control mechanisms have exercised fine grained control in the two dimensions: 1) Time granularity at which power level is changed, 2) Magnitude granularity by which the power level is changed. In our work[2] [12], we investigated the following questions: *Is fine-grained power control really useful and would lead to a better design of power control algorithms? If not, what is the minimum granularity of power control that is useful in different wireless environments, including Internet oriented wireless communication?*

We collected extensive traces from multiple environments such as office building and university departments, to characterize Received Signal Strength Indicator (RSSI) variations in different indoor settings. Through rigorous statistical analysis of the traces using Allans Deviation (for characterizing the burst size of RSSI fluctuations) and Normalized Kullback-Leibler Divergence (NKLD) (for characterizing RSSI distribution in real time), we observe that the number of feasible power levels that can be used in a transmit power control mechanism is few and discrete, and once identified, could be used to perform power control at small time scales (per packet). For example, Figure 3 shows the probability density function of RSSI distribution for various power levels at the transmitter for outdoor and indoor experiments. The power levels are increased from 10mW to 60mW (max. transmit power), in steps of 10mW. For the sake of clarity, these power levels are chosen so that there is minimal overlap between their respective RSSI distributions. This figure shows that a significant overlap between the RSSI distributions of two (successive) power levels correspondingly exists and this diminishes the practical effect of having the respective distinct power levels they become practically indistinguishable at the receiver. Therefore, fine grained transmit power control mechanism are much more difficult to realize especially in indoor deployments as in enterprise environments.

RSSI values of neighboring power levels tend to overlap significantly in indoor scenarios, with some indoor settings more prone to multipath effects (like cubicles) than others (like large conference halls). Similarly the interference and other factors that determine the extent of RSSI variations will be different for different indoor environments. Hence, it is possible that some indoor environments may allow more power levels to be distinguishable (where RSSI variations are low) as compared to others (where RSSI variation is high). We presented in [12] an empirical model for transmit power control, Model-TPC, that outputs the set of feasible (non-overlapping distribution) power levels for a given indoor setting. This model is computed and adjusted dynamically as wireless data communication is going on.

To validate our model, we pick an existing algorithm [8] that uses transmit power control for improving client throughput and spatial re-use. The algorithm proposed increases transmit power in steps and measures signal quality to ascertain the optimal power setting for a given client. At a high level, the algorithm operates as follows. It starts with the lowest power level and performs normal data rate adaptation using Onoe [9](a standard data rate adaptation mechanism). Once the data rate stabilizes around a value, the power level is increased and the rate adaptation process is continued. This process is repeated until the transmitter reach the maximum rate available or reaches the highest power level. To demonstrate the benefits of our proposed model, we create a set of useful power levels through Model-TPC and restrict the above algorithm to use only this set of power levels in its adaptations. We then compare the adaptation performance of the algorithm under two different scenarios: (i) which uses all possible power levels as available from the wireless interface, and does not use our model-TPC, and (ii) which uses the power levels provided

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[2] This work was done in collaboration with WiNGS Laboratory in University of Wisconsin (http://www.cs.wisc.edu/wings/)

by Model-TPC. Figure 4 presents the cumulative distribution function of the instantaneous throughput (measured every 100 ms) of the two variants of the transmit power control algorithm. The figure shows that using Model-TPC to restrict power levels lead to higher instantaneous throughput for a significant part of the experiment.

REFERENCES

[1] John C. Bicket. Bit-rate selection in wireless networks. *Masters Thesis, MIT*, 2005.

[2] J. Bolliger and T. Gross. Bandwidth monitoring for networkaware applications, 2001.

[3] P. Gupta and P. Kumar. Capacity of wireless networks. In *IEEE Transactions on Information Theory*, 2000.

[4] G. Holland, N. Vaidya, and V. Bahl. A rate-adaptive MAC protocol for multihop wireless networks. In *Proceedings of Mobicom*, 2001.

[5] V. Bharghavan J. Monks and W. Hwu. A power controlled multiple access protocol for wireless packet networks. In *INFOCOM '01*, 2001.

[6] A. Kamerman and L. Monteban. WaveLAN II: A high-performance wireless LAN for the unlicensed band. *Bell Labs Technical Journal*, 1997.

[7] Mathieu Lacage, Mohammad Hossein Manshaei, and Thierry Turletti. IEEE 802.11 rate adaptation: A practical approach. In *Proceedings of MSWiM*, 2004.

[8] K. Leung and L. Wang. Controlling QoS by Integrated Power Control and Link Adaptation in Broadband Wireless Networks.

[9] Onoe Rate Control. http://madwifi.org/browser/trunk/ath_rate/onoe.

[10] P. Shankar, T. Nadeem, J. Rosca, and L. Iftode. Cars: Context-aware rate selection for vehicular networks. In *The sixteenth IEEE International Conference on Network Protocols (ICNP 2008)*, 2008.

[11] Anmol Sheth and Richard Han. SHUSH : Reactive Transmit Power Control for Wireless MAC Protocols. In *WICON '05*, 2005.

[12] Vivek Shrivastava, Dheeraj Agrawal, Arunesh Mishra, Suman Banerjee, and Tamer Nadeem. Understanding the Limitations of Power Control for WLANs. In *The Seventh ACM Internet Measurement Conference (IMC 2007)*, 2007.

[13] Starsky H.Y. Wong, Hao Yang, Songwu Lu, and Vaduvur Bhargavan. Robust rate adaptation for 802.11 wireless networks. In *Proceedings of Mobicom*, 2006.

[14] Chi-Hsiang Yeh. IPMA: An interference/power-aware mac scheme for heterogeneous wireless networks. *ISCC*, 2003.