Goodput Enhancement of VANETs in Noisy CSMA/CA Channels

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Abstract—The growing interest in vehicular ad hoc networks (VANETs) enables decentralized traveler information systems to become more feasible and effective in Intelligent Transportation Systems (ITS). Major challenges in such network environments include varying path characteristics and vulnerable channel quality resulting from dynamic traffic conditions and the design of the road. This paper demonstrates a feasible methodology that can enhance inter-vehicle information dissemination using dynamic optimal fragmentation with rate adaptation algorithm (DORA). DORA achieves maximum goodput in wireless mobile networks by computing a fragmentation threshold and transmitting optimal sized packets with maximum transfer rates. To estimate the SNR in the model, an adaptive on-demand UDP estimator is designed to reduce estimation overhead. Several test-beds were developed to evaluate DORA’s performance in channel estimation accuracy, ad hoc network throughput, and vehicle-to-vehicle network throughput along I-85 in Atlanta, Georgia. The proposed algorithm is an energy-efficient, generic CSMA/CA MAC protocol for wireless mobile computing applications, and enhances system goodput in ad hoc networks and vehicle-to-vehicle networks without modification of the base protocols.

Index Terms—Goodput, Fragmentation, Vehicular Ad Hoc Networks, CSMA/CA MAC

1 INTRODUCTION

The IEEE 802.11 technology has been significant successful in deploying inexpensive wireless access to provide high data rates in comparison to the cellular technologies. Theoretically, IEEE 802.11b [1] can achieve 11 Mbps. However, the unlicensed spectrum is inherently open to interference from codeless phones, TVs, and microwaves, causing the actual throughput to be far less than 11 Mbps. To support higher rate data transmission, IEEE 802.11a [2] was proposed. Even though the spectrum is not as crowded as the 802.11b frequencies, the line of sight propagation characteristics prohibit achieving the theoretical maximum throughput. Typically less than 20 Mbps can be obtained within 25-meter range. To avoid the large propagation loss and the line of sight characteristics, the IEEE 802.11g [3] standard has been finalized to support 802.11a/b physical layers at 2.4 GHz. However, it uses the same congested spectrum, and reduces the data rate to the 802.11b rate in the presence of 802.11b participants in the network.

Vehicular ad hoc networks (VANETs) are an application of mobile ad hoc networks that provide communications between vehicle to vehicle or vehicle to roadside in short to medium ranges. Short-range vehicular communications can be established for the Dedicated Short Range Communications (DSRC) using IEEE 802.11p [4] specifically Wireless Access in Vehicular Environments (WAVE). These technologies are efficient to exchange data between vehicles and/or road side nodes in the licensed 5.9 GHz band. Since the range of these protocols can be extended to medium range using mobile multi-hop ad hoc networks, it is important to adapt the physical and medium access control (MAC) layer properties to complete data transaction in very short time for high-speed vehicle communications.

Many algorithms and technologies have been proposed to improve the performance of the IEEE 802.11 networks. Rate adaptation schemes are to increase the throughput by changing the transmission rate to the maximum rate of the time varying wireless channels. The auto rate fallback (ARF) protocol [5], which selects the transmission rate of the sender based on how many consecutive successful transmissions have been received, was adopted in the commercial product, Lucent WaveLAN II. However, the ARF protocol is inherently limited in that it simply counts the number of successful and unsuccessful transmissions to decide next transmission rates. The receiver-based auto rate (RBAR) [6], on the other hand, uses handshaking for exchanging link quality. The receiver estimates the channel from the received signal strength of the request-to-send (RTS) frame, and sends this information in the modified clear-to-send (CTS) header to the sender for selecting the next transmission rate. However, this approach always requires RTS/CTS exchange, and sacrifices bandwidth in the network. In addition, the protocol modification makes it difficult to be deployed in reality. The opportunistic auto rate (OAR) [7] extends the RBAR such that it ensures the same time-shares for all nodes. In a good channel, it opportunistically sends more packets while maintaining the same channel access time.

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Nevertheless, it has the same inherent problems of protocol modification and bandwidth waste as the RBAR.

Packet length adaptations are approaches that have been studied to increase throughput by changing the frame size to match the time varying wireless channels. The architecture for adapting frame length to a time varying channel is proposed in [8]. It exploits the effect of bit error rate and frame length on throughput in wireless network. Simple backoff based frame length adaptation [9] is proposed to adapt fragment sizes using the fragmentation threshold in time varying error prone channels. In this algorithm, the next fragment is set to half of the previous one, if an acknowledgement (ACK) is lost or timeout occurs. When the transmission is successful, it is doubled in the next stage. Similar approaches [10] [11] have been proposed to tune fragment size to fit in a dwell time in the frequency hopping system. However, these approaches are for a general MAC protocol. In [12] [13] and [14], a link adaptation strategy is studied to select the optimal combinations of the 802.11 PHY mode and the fragment size to achieve the best throughput performance for different SNR conditions. These approaches have a detailed analysis of the medium access protocol with fragmentation, and show how the fragmentation affects throughput with different physical modes and SNR. Although the scheme achieves some degree of optimization, it excludes the effect of collisions and thus applicability is limited to a single user case. Furthermore, the assumption that the received signal strength (RSS) has a linear relationship with the SNR of the receiver is not valid even though there is no interference or hidden terminals at the receiver. Since uplink and downlink channels are not always symmetric even in the line of sight propagation path, the SNR estimation by only using the observed received signal strength is not enough to track the time varying wireless channels. J. Yin et al models the effect of the contentions among users, the collisions, and the random errors at the receiver in [15]. In the analysis, the optimum packet size is computed in an error prone channel. However, if arbitrary sized packets can be fit into the optimum sized packets remains unexplained. If fragmentation is performed in MAC layer, the computation of the optimal fragment length would be different due to fragmentation overheads and time spent for transmitting fragmented frames. In addition, obtaining the bit error rates and SNR of the receiver is not elaborated in the literature. Rate adaptive protocol with dynamic fragmentation [16] combines fragmentation with existing rate adaptation schemes. Basic operation of the protocol is similar to RBAR [6] in that it exchanges channel information using modified RTS/CTS packets. When using fragmentation, the time duration for transmitting each fragment is equal to each other by adjusting the length of each fragment to available rates. For example, if a channel becomes better during the fragmentation process such that the next transmission rate is doubled, the next fragment length is also doubled to send twice as much data, while the time spent to transmit those two fragments remains the same. Although, this algorithm achieves much better throughput compared to RBAR [6], it has the same problems of rate adaptation approaches. In addition, the typical WLAN channel is slow fading, and the channel coherent time is long enough to hold multiple packet transmissions. Therefore, actual performance benefit of this algorithm in a typical indoor WLAN is limited, while incurring control packet overheads and protocol change in existing deployed 802.11 systems.

In this paper, we propose a dynamic optimal fragmentation with rate adaptation (DORA) algorithm to improve vehicle-to-vehicle ad hoc communications of the noisy CSMA/CA wireless channels without changing protocols. The algorithm adapts packet lengths and transmission rates dynamically to select optimum values, and maximize the goodput in time varying noisy vehicular mobile environments. The algorithm adopts an adaptive estimator with on-demand UDP updates designed to estimate the SNR of the receiver while reducing frequent message overheads between vehicles. The performance of the proposed algorithm is verified in a static three-hop ad hoc network, and is applied to vehicle-to-vehicle communications on I-85 in Atlanta, Georgia. The remainder of this paper is structured as follows. An overview of the CSMA/CA MAC in 802.11 is presented with an analysis of fragmentation and goodput in the following section. The optimal fragmentation and rate adaptation algorithms are discussed with channel estimation in Section 3. Considerations and issues for real time implementation of DORA are elaborated. Then we describe our experiments performed in a three-hop ad hoc network and vehicle-to-vehicle communications with a discussion of the validation of the SNR estimator in residential and highway mobile environments. Finally, we conclude with discussion in the last section.

2 CSMA/CA MAC

2.1 CSMA/CA MAC Overview

The fundamental access method in the IEEE 802.11 is a carrier sensing multiple access/collision avoidance (CSMA/CA) mechanism to avoid collisions in the medium while users contend to access the channel. If contention free access is required, point coordination function (PCF) built on the top of the DCF is provided.

In DCF, stations sense whether the medium is idle or occupied by other stations before sending data. If the medium is idle for a DCF inter-frame space (DIFS) interval, the station decreases its backoff timer, which is randomly selected at the first attempt of the transmission. When the backoff timer expires, it transmits data. If the transmission is successful, the station resets the backoff timer and chooses a new time slot in the contention window. A station that has failed the first round of transmission should exponentially backoff the contention window and retry later when the medium is idle. This exponential backoff of the contention window will repeat until it reaches its maximum of 1023 slots for the 802.11b direct sequence spread spectrum (DSSS) physical layer as in Fig. 1. Then it remains there unless the timer is reset by a successful transmission, or discarded by the retry counter. Because DCF operates without a central coordinator, the medium access control is done independently. This typi-
Fig. 1. Exponential backoff of the contention window.  

Fig. 2. Basic access method and inter frame space.  

Fig. 3. Probability of errors and BER.

with rate adaptation with low complexity, we use a practical model suggested in our previous research [18] and [19]. This model is a simple but comprehensive analytical model that considers fragmentation overheads and time intervals. Even though the methodology to derive the formula is similar to [15], the actual computation of the optimal sizes is different due to fragmentation overheads and time components. Furthermore, packet lengths and transmission rates are changing dynamically in DORA while [15] is a simple calculation of the packet lengths in static environment.

The key assumption of our model is that the unsuccessful transmission probability, which is the resultant from collisions or corrupted random bits, is a constant and independent probability seen by a packet being transmitted in a randomly chosen time slot. Thus, each time a station transmits a packet, the unsuccessful transmission probability is constant at steady state in a generic slot. This is a valid assumption if backoff stage of the whole system with nodes and random bit errors is at steady state. The details of the assumptions and derivation of the model can be found in our previous study in [18] and [19].

In terms of fragmentation overhead and random packet loss, suppose an $L$ bit long MAC Service Data Unit (MSDU) is fragmented into $j$ MAC Protocol Data Units (MPDUs), and denote $L_{opt}$ for the length of the fragmented MPDUs. Subsequently, it incurs $j-1$ times the additional overhead of $H + 2 \text{SIFS + ACK}$, where $H$ is the header of the MSDU. Note that this overhead is additive, while the probability of packet loss is reduced exponentially from $1 - (1 - p_b)^j$ to $1 - (1 - p_b)^{L_{opt}}$, where $p_b$ is bit error rate in the channel. This packet loss caused by wireless random errors has an immense impact on the probability of unsuccessful transmission, especially when
the channel becomes worse. As illustrated in Fig. 3, the probability of packet loss is the dominant factor when the BER is $10^{-4}$, whereas the probability of collision is the major component of the unsuccessful transmission probability at a moderate BER of $10^{-5}$. For the same MPDU length with the same number of users, the probability of collision at $10^{-4}$ is smaller than that of $10^{-5}$. In other words, the probability of collision is lower in a bad channel for the same MPDUs than in a good channel. The rational is that the probability of unsuccessful transmission increases as the channel becomes worse due to the influence of the random errors, which causes a transmission failure and exponential backoff, resulting in larger average waiting time. Therefore, the probability of collision is lower in this bad channel. However, since the probability of packet loss is greater in this channel, the overall probability of unsuccessful transmission is also greater, and the goodput decreases severely as the channel quality becomes worse.

From our previous work [18] and [19], we have goodput $G$

$$G = \frac{P_s \cdot (1-P_s) \cdot T_s}{T_c + P_s \cdot (1-P_s) \cdot T_c + (1-P_s) \cdot T_s + P_s \cdot P_c \cdot T_c}$$

where $P_s$ is the probability of successful transmission without collision and $P_c$ is the probability of the packet loss by random bit errors in $L$ bit packet. For the time components, $T_i$ is the average idle time between two consecutive transmissions, $T_c$ is the time needed to detect collision at the receivers, $T_i$ is the time duration normalized to a slot time to transmit user data, and $T_f$ is the time interval to send $L$ bits successfully with fragmentation. Given a packet size $L$, the number of users $n$, and a BER, the solution, optimal fragment $L_{opt}$, of the nonlinear system (1), can be uniquely determined using numerical approaches to find where $G$ reaches the maximum value.

The optimal MPDUs for 1500 bytes MSDU are illustrated in Fig. 4 with various BERs and number of users for 1Mbps modulation rate in 802.11b. In a perfect channel with less than 10 users, fragmentation has no positive impact on goodput. Since the probability of random packet loss is negligibly small in this channel, the probability of unsuccessful transmission is almost equal to the probability of collisions. If the channel is perfect, the probability of collisions is not a function of packet length, but a function of number of users in the network. Therefore, if there is no hidden terminals and interference at the receivers, and all stations obey the basic access rules, a constant probability of collisions is expected regardless of the packet length, and the performance will be degraded gracefully. However, the probability of collisions increases as the number of user increases. As the contentsions become severe, a longer packet needs more time to detect loss and recover from it. In such cases, the optimal fragmentation technique can provide more benefit by adjusting the fragment size to the channel.

As the channel becomes worse due to random packet drops, the fragment size should decrease abruptly to compensate for the random errors. The contention among users also affects the optimal MPDUs as mentioned earlier. However, the impact of the contention is minor, since random errors play a bigger role on the exponential backoff procedure than collisions caused by contentions. Consequently, optimal fragmentation improves goodput more effectively as the channel becomes worse, or the number of users increases in the network. We present the performance of using the optimal fragmentation in Fig. 4 and Fig. 5 for the 1 Mbps 802.11b physical mode.

3 SYSTEM DESIGN

Optimal fragmentation significantly improves goodput in a typical wireless environment. To apply optimal fragmentation dynamically in time varying channels, the sender should be informed of the SNR of the receiver. Dynamic optimal fragmentation with rate adaptation (DORA) uses the on-demand adaptive SNR estimator with network parameters to select the maximum rate and the optimal fragmentation. The network parameters considered in the model includes the incoming packet length, BER, number of users, and the transmission rates. In this chapter, design considerations to implement DORA will be discussed with rate adaptation and channel estimation algorithm.
3.1 Optimal Fragmentation

The optimal fragmentation enhances goodput in typical wireless environments as described earlier. The actual values to be used in the system should consider MAC header and SNAP header. Assuming the optimal fragment, \( L_{opt} \), is 500 bytes for 1500 bytes MSDU, the fragmentation threshold should be 528 bytes taking into consideration of the 28 bytes of the MAC header. An additional 8 bytes of SNAP header needs to be carried. Therefore, three 531 bytes MPDUs that can carry 9 additional bytes of SNAP header needs to be carried. Thereby, the overall rate threshold to be used in the system should consider MAC headers. An additional 8 bytes of SNAP header should be the fragmentation threshold to be used in the system.

The problem is how to monitor these parameters in real time, such as incoming packet length, BER, number of users, and transmission rates, in order to decide the optimal fragmentation threshold without modifying the protocols. The packet length and the number of users are known parameters in the network. For the BER and transmission rates, a new rate adaptation algorithm is proposed to incorporate transmission rate with the optimal fragmentation to meet the desired BER or packet error rate (PER). In the following section, DORA rate adaptation is elaborated.

3.2 Rate Adaptation

Since different modulation schemes support different rates, the rate can be adjusted to improve network goodput by switching to a higher modulation scheme if channel conditions improve. Fig. 6 illustrates the BER vs. SNR curves for various modulation schemes in conventional rate switching technique and DORA. The BER vs. SNR curves can be found for 802.11 physical modes in [20], [21] and [22]. The target BER can be maintained by simply switching rates. With the consideration of the rate for a given SNR in Fig. 6, the rate \( R \) may be written as

\[
R = \min \{ \frac{SNR}{SNR_{opt}}, \frac{SNR_{opt}'}{SNR'} \}
\]

(2)

where \( SNR_{opt} \) is the minimum SNR to meet the target BER with the rate \( R \). However in DORA, the SNR range for the same transmission rate can be further shifted down to lower SNR range, if the optimal fragmentation improves the goodput such that the same goodput in the conventional rate switching can be obtained by DORA. That is

\[
R_{opt} = \min \{ \frac{SNR_{opt}}{SNR_{opt}}, \frac{SNR_{opt}'}{SNR'} \}
\]

(3)

where \( SNR_{opt}' \) is the minimum SNR to achieve the same goodput for the conventional rate \( R \). This rate switching can reduce the energy to be transmitted for the nodes, and increase the overall network goodput by reducing the interferences adjacent to the nodes.

3.3 Adaptive Channel Estimation

The challenging problem of SNR based rate switching and other approaches that use SNR of the receiver to obtain the SNR, which is not supported in the 802.11 CSMA/CA MAC standard. In [6], [7] and [16], a modified RTS/CTS exchange is used to feedback the channel conditions of the receiver, which requires modifications of the protocol. The link adaptation strategies [12], [13] and [14] use the received signal strength (RSS) of the frame from the access point to select the best transmission rate for the sender. This approach assumes that the RSS has a linear relationship with the SNR of the receiver. However, this assumption is not valid when the AP supports multiple rates for downlink channels. Since mobile nodes may have different network cards, the transmission power of each user may be different. Therefore, SNR estimation with RSS for each station should be different, and the AP is not able to select proper rates individually for the stations. Furthermore, in the presence of interference at the receivers, strong RSS at the AP does not guarantee better SNR, and each user may experience different profile of interference.

The adaptive estimator in DORA uses on-demand, low overhead UDP messages to avoid modification of existing protocols. In the estimator, the received signal strength from the receiver is defined as \( y(k) \). Suppose any mobile stations can overhear \( y(k) \) as long as they are in the communication range. If the average received signal strength up to \( k-1 \)th frame is denoted as \( \overline{y}_{RSS}(k-1) \), and the SNR estimation of the \( k+1 \)th frame is defined as \( \hat{y}_{SNR}(k+1) \), the estimation of the SNR at the receiver can be represented as

\[
\hat{y}_{SNR}(k+1) = (1-\alpha)\overline{y}_{RSS}(k-1) + \alpha y(k)
\]

(4)

where \( \overline{y}_{SNR}(k) \) is the average SNR of the receiver, and \( 0 \leq \alpha \leq 1 \). The term, \( \gamma \geq 0 \), is to decide how much moving average of the received signal strength will be added to the average SNR of the receiver in the estimation. Given that the uplink and downlink channels are not always geographically symmetric, the estimation by only using the observed received signal strength is not valid.
for selecting $L_{opt}$ and $R_{opt}$, even though there is no interference or hidden terminals at the receiver. In Fig. 7, the difference between SNR of the receiver and the RSS at the sender can be observed for the same transmission power of -10dBm with LOS in a typical office environment. Total 50 packets of 1500 bytes MSDU are used to measure the SNR of the receiver and RSS at the sender for the same noise power using the MadWifi driver. However, the received signal strength is not totally irrelevant to the SNR of the receiver either. It provides a rough figure of the SNR in different time scale and amplitude in dB. Thus, the adaptation algorithm should be informed of the initial average SNR of the receiver in any forms so that it tracks the SNR while reflecting the variation of the RSS on it. Details of the estimation algorithm are illustrated using the state diagram in Fig. 8.

The receiver informs the sender of $\bar{y}_{SNR}(k)$ using UDP messages in two events, i.e., when the difference between the averages of SNRs is greater than $\Delta_{SNR}$ (i.e., $|\bar{y}_{SNR}(k-1) - \bar{y}_{SNR}(k)| \geq \Delta_{SNR}$), or $\bar{y}_{SNR}(k)$ stays longer than the channel coherence time $T_c$. The time duration over which the channel impulse response is essentially invariant. That is

$$T_c = \frac{9}{16 \pi f_m^2} = 0.423, \tag{5}$$

where $f_m$ is the maximum Doppler shift. $T_c$ may vary with respect to the BER performance of the modulation schemes and maximum Doppler shift. How quickly the estimator tracks the SNR can be determined by choosing the parameters $\alpha$, $\gamma$, $\Delta_{SNR}$ and $\Delta_{coherence}$ in the equation (4). However, finding optimal parameters to tune the estimator for a typical wireless vehicular-to-vehicular environment is a demanding task that requires experiments and field trials. We performed heuristic approach to select the parameters based on our experiments and observation.

For the messaging overhead of UDP messages, even if the SNR varies severely in the channel, we have found that the estimation overhead produced by the on-demand UDP messages in the estimator yields less than a two-byte message in a second in general. These UDP messages, nevertheless, can still influence the system goodput, and sacrifice bandwidth in the network. In Fig. 9, the influence of the UDP messages on the system goodput is described. Each vehicle transmits UDP control messages to estimate the SNR of the receiver during the TCP transmission with 1500 bytes MSDU for 4% of packet error rate in NS-2 simulator. Even in the worst situation of 30 users with one UDP messages in a second, the performance loss is less than 1.6% compared to the normalized goodput of the basic operation, while RTS/CTS based channel estimation in [6], [7] and [16] introduces 11% of the loss. Further overhead reduction can be made by adjusting parameters in equation (4), if a coarse estimation is more desirable by sacrificing the accuracy in certain circumstances. In most cases, the average of less than one UDP messages per second can be obtained in the vehicle-to-vehicle communication by using the on-demand UDP estimator. Nevertheless, the total performance gain that DORA achieves is greater than basic operation as described earlier in Fig. 5.

### 3.4 Other Considerations

The SNR of the receiver is one of the most important components in the calculation of $L_{opt}$ and $R_{opt}$. DORA uses on-demand adaptive estimator instead of using an explicit SNR feedback as in [6], [7] and [16] to decide optimum values in the channel. Note that the target bit error
rate or symbol error rate in SNR based rate switching are fixed. If the SNR fluctuates severely such that the BER also changes dramatically, the optimum rate adaptation automatically switches the transmission rate to a higher or lower rate in order to maintain the target BER or SER. Furthermore, selecting wrong optimal fragmentations are unlikely as the estimation algorithm has a very low approximation error (e.g., average of 0.373 dB for 6,000 samples in our experiment). For example, assume 750 bytes of optimal MPDU for 15 mobiles at the BER of $1 \times 10^{-5}$ in Fig. 4. If 500 bytes MPDU, which is the optimal value for the channel $3 \times 10^{-5}$, is selected due to the under estimation of the SNR, at least 1.1dB of SNR estimation error is required. However, 500 bytes MPDUs still achieve 99.98% of the goodput against the optimal value, 750 bytes. In case the optimal fragmentation selects 1500 bytes, it would transmit larger frames in a bad channel, and it loses 9% of goodput. However, that hardly occurs in the proposed adaptive estimator, since the estimator would need to over estimate at least 4.61 dB.

In the non-linear system given by (1), senders must determine $L_{\text{opt}}$ and $R_{\text{opt}}$. Obtaining $R_{\text{opt}}$ is straightforward if the senders can estimate the SNR precisely for a given target BER or SER. However, solving (1) to get $L_{\text{opt}}$ in real-time is a computationally expensive task. By incorporating the knowledge that $L_{\text{opt}}$ is a divisor of the original packet length, further simplification can be made to alleviate the complexity of the system for the real time implementation. For example, if the packet is 1500 bytes, the valid candidates of $L_{\text{opt}}$ are 1500, 750, 500, and 300 bytes in Fig. 4. This enables the system to use a small, efficient lookup table to determine $L_{\text{opt}}$. Further reduction can be made to decrease the complexity of the system without performance degradation by setting a minimal packet length considered for fragmentation. In DORA implementation, 300 bytes MPDU is the minimum frame length, and any frames less than 600 bytes will not be considered for fragmentation.

For network security, it is the sender that computes $L_{\text{opt}}$ and $R_{\text{opt}}$. Thus, if associated receivers are trusted entities, it would not introduce security problems. Additionally, senders could be any of the wireless stations, i.e., client stations and access points in WLAN, or wireless mobile stations in a multi-hop ad hoc networks and vehicle-to-vehicle networks.

### 4 Experiments

To verify the goodput performance of DORA in vehicular ad hoc networks, experiments for the channel estimator are first executed with two vehicles on Interstate-85 North Exit 99 to 102 in Georgia and in residential areas in Atlanta. Verification of existence of optimal MPDUs in ad hoc networks is performed with four ad hoc stations without mobility behavior in order to remove uncertainties depending on mobile environments. Finally, we experimented implemented DORA in VANETs on I-85 North in Georgia and compared the goodput with auto rate fallback algorithm [5].

#### 4.1 On-demand Adaptive Channel Estimator

Real time SNR estimation is executed for the passing and crossing scenarios. External antenna shown in Fig. 11 is connected to the Proxim 802.11b card, and placed using magnetic base in the center of the roof of the car. To record exact location and speed of the vehicles during the experiment, a GPS antenna [24] with HP iPAQ pocket PC is installed in each vehicle. To supply power for the mobile node and the GPS device in each vehicle, 200-Watts power inverter is used with a UPS. For the mobile stations, Ubuntu 6.10 [25] operating system is installed with the MadWifi driver. The MadWifi driver supports the network configuration of the mobiles and provides SNR information, received signal strength, and data received through the network interface. The SNR is transmitted to the sender when $\Delta_{\text{SNR}}$ and $\Delta_{\text{coherence}}$ meet the requirements of the adaptation algorithm described earlier. For the received signal strength from the receiver, the sender can overhear it as long as they are in the communication range. Default transmission power of the card, 17 dBm is used for the communication between the sender and the receiver.

For the parameters in the estimation, $\alpha$ and $\gamma$ are set to 0.9 respectively. Based on our experiments and observations, we heuristically select $\Delta_{\text{SNR}}$ and $\Delta_{\text{coherence}}$ to 0.2 dB and 0.1dB. The SNR and the RSS are sampled in every 10 ms, and the average of 50 samples are used to calculate $\overline{y}_{\text{RSS}}(k-1)$ and 20 samples for $\overline{y}_{\text{SNR}}(k)$ respectively. The channel coherence time, $T_c$ is set to 50 ms.

For the first passing scenario, the sender in the first lane passes the receiver in the last lane in Fig 10. The initial distance between each vehicle is approximately 200
meters. The average speed of the receiver is approximately 58.4 mph while the sender passes the receiver with the average speed of 70.4 mph. The channel is saturated by 1500 byte MSDU in TCP connection, and the SNR is measured by polling iwspy from the driver in every 10 ms. In Fig. 12, the estimation tracks the SNR of the receiver with only 46 UDP messages in 60 seconds. This is extremely low overhead when considering the typical passing scenario in highways with trucks, different curvature and elevation of the road. Normally, just a 2 bytes UDP message is enough to represent the SNR for 0.1dB scale. Detailed behavior of the vehicles is depicted in Fig. 13.

For the second scenario, two vehicles cross each other in residential areas shown in Fig. 14. All the parameters in the estimator are the same as the first passing scenario. The average speed of the vehicles is approximately 38 mph in opposite directions. Thus, there is 76 mph speed difference, and this will introduce severe Doppler frequency shift and SNR variation compared to the previous experiment. The estimation results are depicted in Fig. 15 and Fig. 16. The peak SNR of the channel reaches approximately 30 dB when the two vehicles are crossing each other, and it is roughly the same as the previous passing scenario. However, the time duration that may ensure reliable connection between the vehicles is much shorter than the previous passing scenario. For example, the time interval that the SNR exceeds 20 dB for the crossing scenario in residential areas is just 20% of the passing scenario in highways. Thus, crossing vehicle-to-vehicle communication in highways is much more susceptible to the link failure, and it produces challenging routing problems to be solved in a short time.

4.2 Ad Hoc Networks

Ad hoc is a network that requires no infrastructure to form connections to transmit data among the nodes in the network. The stations within range can discover each other to form a routing path by flooding or forwarding information to the other nodes. Thus, the network connections can be extended to multiple nodes to transport data through the routing path dynamically. If the nodes in the routing path move to the outside of the network, a new routing path is established to maintain connections using routing algorithms. These types of networks are very effi-
For the maximum achievable goodput in a perfect channel, the nodes are placed such that the average SNR of each link is 21.3 dB. Theoretically this SNR exceeds approximately 6 dB more than the bit error rate of $10^{-7}$ in the BER equations found in [20] for an additive white Gaussian noise channel. The AWGN channel model is not realistic in vehicular ad hoc networks, but this model is useful for reference purposes, since no exact channel model for the experiment is available. For DBPSK,\[
P_{DBPSK} = \frac{1}{2} e^{-E_b/N_0},
\]where $E_b/N_0$ is the SNR per bit. Each node has the transmission power of 20 dBm, and links between each adjacent station has 85 dB path loss. The sender generates 1500 bytes of MSDU, and establishes a TCP flow to the receiver through the wireless nodes in the ad hoc routing path. With poisson-distributed inter-departure, the sender transmits 60 packets per second on average to the receiver, which is enough to saturate a three-hop ad hoc network. Then, the 1500 bytes MSDU are fragmented into MPDUs to find the optimum fragment, $L_{opt}$. For each fragmentation threshold, 20 trials of 50 seconds per trial are executed for MPDUs of 300 through 1500 bytes in each given BER.

For a typical wireless channel, the transmission power in the second experiment is reduced to 10 dBm with the same topology configurations. This yields an average SNR of 11.1 dB, which has an offset of 0.3 dB from the BER channel of $10^{-5}$ in (6). The results in Fig. 18 clearly show two distinct performance differences between the perfect channel and a typical wireless channel. Contrary to the expectation that the goodput is higher in the perfect channel, the average goodput for each MPDU in a perfect channel is lower than the one in a typical channel by 91.3 kbps for 1 Mbps DBPSK modulation. The rationale of the fact is that by increasing SNR between links, the random packet drops can be reduced significantly. However, strong signals introduce severe interference to the adjacent links, and prohibit the other stations in the routing path from routing the packets at the same time.

The analytical model (1) considers one-hop link goodput of CSMA/CA MAC protocol. The number of end-to-end hops in ad hoc networks has a direct impact on the goodput. We consider TCP at a steady state with no queuing and processing delay. The end-to-end throughput of the multi-hop string topology is inversely proportional to the round trip time (RTT). In the perfect channel in Fig. 17 for the BER of $10^{-7}$ with 20 dBm transmission power, the signal power of each node is strong enough to prevent other nodes from routing packets. Therefore, the RTT will increases approximately three times for a three-hop string ad hoc network, and goodput drops to roughly the one third compared to that of the one-hop link. How-
ever, by reducing the transmission power to 10 dBm to obtain the BER of $10^{-5}$, when the first node transmits to the second node, the fourth node can simultaneously transmit packets to the third node. Similarly, the second node can transmit to the first node while the third node is sending packets to the forth node. Thus, the effective RTT is two times larger than the one-hop link, and the goodput drops to half of the analytical one-hop model (1). A general analysis of TCP throughput in the IEEE 802.11 multi-hop ad hoc network can be found in [26].

Analytical reference curves obtained by (1) are drawn with the experiment results for a three-hop ad hoc network in Fig. 19. As the model (1) is a function of the MPDU length as well as the SNR of the channel for goodput, the three-hop ad hoc network has similar trend with different scale due to the different number of hops in the path and transmission power that introduces different adjacent channel interference. Therefore, proper selection of the routing path with power control is important in ad hoc networks to improve goodput, and optimal fragmentation performs better in this low SNR channel with less transmission power. As a result, $L_{opt}$ increase goodput by 48.1% and provides a routing algorithm with enhanced energy efficiency. Further research can be performed to find the optimal routing path that maximizes goodput using this technique. Note that DORA optimizes one-hop wireless links rather than end-to-end routing paths and provides the maximum achievable goodput for each link of the established routing path. However, this path may not be the best route in terms of maximum goodput. Therefore, finding the best routing path that incorporates individual optimized links to the last-hop is a challenging problem due to difficulty of exhaustively searching for all possible routing paths among many nodes in dynamic mobile ad hoc networks. An analysis of end-to-end performance along the optimized links in ad hoc networks with TCP interaction can be considered for future research as well.

![Fig. 19. Goodput vs. MPDU in a three-hop ad hoc network with analytical references.](image)

4.3 Vehicle to Vehicle Networks

Various vehicular communication technologies have been proposed to provide seamless wireless communications. Third generation networks support wide coverage, seamless mobility, and quality of service for mobile users. However, these connection-oriented networks require expensive infrastructure for deployment, and they are effective mostly in voice traffic applications. Short-range vehicular communications can be established using IEEE 802.11p [4], specifically Wireless Access in Vehicular Environments (WAVE) for the Dedicated Short Range Communications (DSRC). These technologies are efficient to exchange data between vehicles or vehicles to roadside in the licensed 5.9 GHz band. Since the range of these protocols can be extended using mobile multi-hop ad hoc networks discussed in the previous section, it is important to adapt the physical and MAC layer properties to complete data transaction in very short time for high-speed vehicle communications.

The vehicle-to-vehicle mobile experiment consists of four mobile stations equipped with 802.11b network cards as shown in Fig. 20. The network card is externally connected to the antenna, which is placed using a magnetic base on the roof of the car and separated approximately 1 meter from the PC. The same GPS antenna [24] and HP iPAQ pocket PC in the previous channel estimation experiments are installed in each vehicle with the mobile stations running Ubuntu 6.10 [25] and MadWifi. All four mobile stations are configured to transmit in the same cell and channel to cause collisions in the network. The on-demand adaptive estimator is used to estimate the SNR of the receiver. The default transmission power of the card, 17 dBm, is used for the communication between the sender and the receiver.

For the performance evaluation in Vehicle-to-Vehicle communication, auto rate fallback [5] (ARF) protocol is used to compare goodput against the proposed algorithm. ARF is a default rate adaptation algorithm implemented in the card. ARF selects the transmission rate of the sender automatically based on how many consecutive successful transmissions have been received. This scheme has inherent limitations in adapting rates to time varying channels.

In the experiments, ARF and DORA senders generate 1500 bytes of MSDU using netcat and establish a TCP flow to the receivers through a one-hop ad hoc routing
The DORA sender selects $L_{\text{opt}}$ and $R_{\text{opt}}$ dynamically using estimated SNR from the on-demand adaptive estimator, while ARF sender transmits normal 1500 bytes MSDU.

Four mobile stations, with GPS, pocket PC, and external antennas, used in vehicle-to-vehicle experiments are shown in Fig. 21. For the performance comparison, extensive experiments are executed in I-85 North Exit 89 to 102 in Georgia. For the estimator, $\alpha$ and $\gamma$ are set to 0.9 respectively. The estimation parameter $D_{\text{SNR}}$ and $D_{\text{coherence}}$ are set to 0.2dB. The SNR and the RSS are sampled in every 10 ms, and the average of 50 samples are used to calculate $y_{\text{RSS}}(k-1)$ and 20 samples for $y_{\text{SNR}}(k)$.

In Table 1, rate selection $R_{\text{opt}}$ with optimal fragmentation $L_{\text{opt}}$ are shown. The BER of DBPSK over an additive white Gaussian noise channel in equation (6) is used to decide $R_{\text{opt}}$ and $L_{\text{opt}}$. The approximated SER of DQPSK found in [21] is given by

$$\text{SER} \leq 2Q\left(\sqrt{\frac{E_s}{N_0}}\right),$$  \hspace{1cm} (7)

where $E_s / N_0$ is the SNR per symbol. The CCK is a variation of M-ary biorthogonal keying (MBOK) modulation for 5.5 and 11 Mbps, and the SER curve can be found in [22]. Based on these approximated SER, $R_{\text{opt}}$ and $L_{\text{opt}}$ can be determined using (1) and (3) such that the system goodput is always maximum over the entire range of the SNR. Note that $R_{\text{opt}}$ in DORA is different from the conventional rate switching. For example, assume the target packet error rate is 8% as described in the standard. When the SNR of the channel improves, conventional rate switching algorithms change the rate from 1 Mbps to 2 Mbps at 18.87 dB to maintain the packet error rate below 8%, which corresponds to the SER of $1.4 \times 10^{-5}$ in 2 Mbps. The maximum goodput of 1 Mbps is 0.833 Mbps up to the SNR of 18.87 dB. In DORA, however, $L_{\text{opt}}$ of 300 bytes at 2 Mbps yields 0.968 Mbps with the symbol error rate of $2 \times 10^{-4}$ at 13.8 dB. Therefore, DORA can switch the rate to 2 Mbps at 13.8 dB to accomplish 0.968 Mbps, which yields 16.2% greater goodput than the maximum goodput, 0.833 Mbps, at 1 Mbps transmission rate. This rate switching technique provides benefits on the selection of a low interference routing path and efficient power management plan for limited battery capacity vehicles transmitting higher data rate.

For the first scenario, the SNR is dropped to a lower SNR after establishing connections between the two vehicles. In the theoretical analysis from [20], [21] and [22], if the SNR is 30 dB, the channel is excellent to transmit and receive data without packet drops. However, mobile environments where cars and trucks are driving highways approximately 60 mph, with different road curvatures and elevations, are very different from the ideal AWGN channel. Therefore, the actual SNR scale for mobile communication differs substantially from the reference models [20], [21] and [22], and adjustment is inevitable to make connections. From the observation obtained in the previous channel estimation experiments, approximately 30dB is a marginal SNR for the mobile communications to exchange data in Interstate-85 EXIT 89 to 102. Thus, in the experiment in Fig. 22 and Fig. 23, on-demand estimator subtracts 20 dB such that actual 30 dB SNR is regarded as 10 dB in the Table 1 for choosing $L_{\text{opt}}$ and $R_{\text{opt}}$.

To measure this scenario, the sender vehicle drives close to the receiver vehicle, and passes the vehicle to the place where the link is barely connected between two vehicles in 30 seconds. Fig. 22 illustrates the SNR of the receiver, the on-demand adaptive channel estimator, rate adaptation, and the goodput of DORA and ARF. The on-demand adaptive estimator tracks the SNR of the receiver.

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**Table 1**

<table>
<thead>
<tr>
<th>SNR (dB)</th>
<th>Rate (Mbps), Fragmentation (bytes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>&gt; 21.8</td>
<td>11, 1500</td>
</tr>
<tr>
<td>19.3 - 21.8</td>
<td>11, 750</td>
</tr>
<tr>
<td>18.6 - 19.3</td>
<td>5.5, 1500</td>
</tr>
<tr>
<td>18.1 - 18.6</td>
<td>5.5, 750</td>
</tr>
<tr>
<td>17.9 - 18.1</td>
<td>5.5, 500</td>
</tr>
<tr>
<td>15.9 - 17.9</td>
<td>5.5, 300</td>
</tr>
<tr>
<td>14.9 - 15.9</td>
<td>2, 1500</td>
</tr>
<tr>
<td>14.3 - 14.9</td>
<td>2, 750</td>
</tr>
<tr>
<td>14.0 - 14.3</td>
<td>2, 500</td>
</tr>
<tr>
<td>13.8 - 14.0</td>
<td>2, 300</td>
</tr>
<tr>
<td>12.2 - 13.8</td>
<td>1, 1500</td>
</tr>
<tr>
<td>10.0 - 12.2</td>
<td>1, 750</td>
</tr>
<tr>
<td>9.25 - 10.0</td>
<td>1, 500</td>
</tr>
<tr>
<td>8.50 - 9.25</td>
<td>1, 300</td>
</tr>
</tbody>
</table>

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Fig. 21. Four mobile stations, GPS, pocket PC and external antennas used in vehicle-to-vehicle experiments.

Fig. 22. Illustration of goodput for 30 dB channel in DORA and ARF.
with an average UDP overhead of 0.94 messages per second. Since the actual SNR of the receiver is around 30 dB, the estimator models it as 10 dB, and the rate adaptation stays at 1 Mbps in this channel. In Fig. 23, detailed behavior of the optimal MPDU selection in DORA is described. The optimal MPDU $L_{\text{opt}}$ follows the shape of the estimation in selecting MPUDs between 300 bytes, 500 bytes, and 750 bytes in 1 Mbps. For the ARF, the connection is barely sustained with the goodput of 0.8 Kbps, while DORA outperforms ARF with 615 Kbps in this low SNR channel. This shows DORA is an effective algorithm in noisy CSMA/CA channels for VANETs.

For the second Vehicle-to-Vehicle scenario, the distance between vehicles are controlled to have approximately 35 dB of SNR in the Interstate 85 North, Exit 91 to 94. The on-demand estimator is adjusted to subtract 25 dB in experiment. The SNR of the receiver, the adaptive channel estimation, and the rate adaptation of DORA are illustrated in Fig. 24. Since the SNR of the receiver is around 35 dB, the estimator assumes it as 10 dB, and the rate is selected to 1 Mbps. The average estimation error of this channel is 0.6 dB with the overhead of 0.95 messages per second.

The largest estimation error for the entire duration of the experiment is 2.3 dB at 4 second. This estimation error switches $L_{\text{opt}}$ from 750 bytes to 1500 bytes, resulting in 4% goodput degradation from the optimal fragment. However, this only occurs when the estimation error is large enough to cross the borderline of the rates and optimal fragments, and causes serious goodput deterioration when the estimation is greater than the actual SNR of the receiver. Using one larger fragment from the optimal value degrades goodput more than using one smaller fragment for the same SNR. Based on the observations and results from the experiments, this estimation error rarely occurs for a very short time. The instantaneous throughput for this time duration, nevertheless, is still equal or greater than ARF. In fact, the results show 74% improvement of the goodput in the period. Overall, the average goodput is 627 Kbps while ARF is 325.6 Kbps as shown in Fig. 25.

For the last scenario, the sender controls the distance to the receiver to maintain approximately 10 dB more than the first 30 dB channel in the Interstate 85 North, Exit 96 to 99. The average receiving power of the signal is approximately eight times greater than the 30 dB SNR chan-
The performance of DORA and ARF is illustrated in Fig. 29. The goodput of DORA is proportional to the SNR of the receiver, while ARF is inconsistent with it. The average goodput can be proportional to the SNR of the receiver. However, explanation of this inconsistency of ARF only with the SNR is not sufficient. Note that dynamically changing traffic and different geometric design of the road such as curvature and elevation can produce different profile of mean excess delay and RMS delay spread. Therefore, multipath components can be considered to anticipate more precise analysis for outdoor wireless mobile channels. In addition, the transport layer protocol in this experiment is TCP, which assumes packet losses are an indication of network congestion. TCP is well known to have inability to hold efficiency in wireless networks, and reacts poorly by reducing the congestion window when packet losses occur due to wireless losses. ARF is more susceptible to the variation of these conditions, while DORA shows enhanced goodput with reliable performance in VANETs. Thorough analysis of TCP interaction with MAC and Physical layer characteristics in wireless mobile channel can be solid foundation for designing effective and reliable wireless network protocols for future generation.

5 Conclusions

In this paper, we have presented an effective way to increase the system goodput of CSMA/CA in vehicular ad hoc networks. Using an on-demand adaptive SNR estimator, the algorithm dynamically selects the optimal fragmentation and transmission rate in time varying channels with minimal overhead. Through extensive experiments, we have found the system enhances the goodput ap-

Fig. 27. Adaptive channel estimation and optimal MPDU selection in DORA for 40 dB channel.

Fig. 28. Illustration of goodput for 40 dB channel in DORA and ARF.

Fig. 29. Performance of DORA and ARF with UDP overhead in Vehicle-to-Vehicle networks.
proximately 48% in a three-hop ad hoc network and 92.6% in vehicle-to-vehicle ad hoc communications. The proposed algorithm is applicable to next generation ITS mobile vehicle-to-vehicle communications, and a realistic approach that can be deployed without modification of the existing standards.

ACKNOWLEDGMENT

The authors wish to thank BongKyong for the simulation, and Ying, JiHwan, and Mi hyeon for driving vehicles and supporting experiments.

REFERENCES


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