Intelligent Link Adaptation in 802.11 Vehicular Networks: Challenges and Solutions

Wenchao Xu, Haibo Zhou, Huaqing Wu, Feng Lyu, Nan Cheng, and Xuemin (Sherman) Shen

Abstract

By providing effective wireless vehicle-to-everything (V2X) communication, it is expected that the Internet of Vehicles will be provisioned, whereby various automotive service requirements could be satisfied (enhanced road safety, improved transportation efficiency, etc.). Despite the successful standardization of 802.11-based communication protocols in vehicular networks (e.g., 802.11p, 802.11af), there remains an essential issue, which is to adjust the transmission rate and mode to match the highly dynamic channel conditions in vehicular scenarios. In this article, we first investigate the requirements for intelligent link adaptation (LA) in 802.11 V2X, and then present a data-driven learning-based LA architecture that fits the road channel characteristics while capturing the quick variance due to the high mobility of vehicular networks. We also propose a reference model to show how the data-driven model can efficiently catch the channel variance and improve the "drive-thru Internet" throughput. Finally, we discuss the opportunities and challenges, which should provide significant reference for the development and standardization of the intelligent LA solution in 802.11 V2X networks.

Introduction

The Internet of Vehicles (IoV) is inevitable, because it performs as a bridge connecting the emerging needs of modern vehicle users (safety concerns, transportation efficiency, etc.) to the rapidly evolving network technologies, including the cellular-based LTE-V2X and the WLAN-based 802.11-V2X [1]. It is predicted that the global vehicle-to-everything (V2X) market will reach US$100 billion in the next few years, with the transmission requirement of more than 30 zettabytes data generated from connected vehicles [2].

To satisfy the emerging requirement of such enormous data transmission, in 2012, IEEE published the 802.11-based standard, referred to as 802.11p, to dedicate the band of 5.9 GHz for vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. The equipment of the Dedicated Short-Range Communication (DSRC) transceiver supporting 802.11p has become mandatory for new vehicles manufactured in North America [3]. In 2016, the Third Generation Partnership Project (3GPP) specified the cellular-based V2X technology to support both direct transmission in small range and wide area communication, compatible with fifth generation (5G) networks. Other than these standard promotions, academia has also considered the possibilities to apply other 802.11 radio technologies for V2X communication. For example, the effectiveness of a normal WiFi network has been demonstrated in the paradigm called "drive-thru Internet," which provides Internet access for drive-by vehicles via communication with a roadside WiFi access point (AP). To expand the transmission range, the TV white space (TVWS) spectrum is utilized to support the 802.11af data pipe for vehicular content delivery [4].

Compared to the cellular one, 802.11-based V2X communication often requires less infrastructure investment and can be deployed flexibly in vehicular conditions, and also provides considerable network performance. For example, 2.4 GHz 802.11 WiFi APs can be placed along the roadside using commercial off-the-shelf products, which are as cheap as US$5 per transceiver model, and can achieve around 10 Mb/s V2I data throughput for vehicles driving up to 35 mph [5, 6]. The recently released TV band 802.11af transceivers can provide 24 Mb/s throughput covering 40 km communication range with better penetration capability and non-line-of-sight (NLoS) connectivity [7]. Other advantages, such as universal compatibility of WiFi devices, spectrum versatility, and easy operation, could strengthen the competitiveness of 802.11-based V2X in the market of connected vehicles.

However, a vital issue that prevents further usage of 802.11 V2X and requires careful consideration is the link adaptation (LA) scheme of the 802.11 transceiver to choose the optimal rate and transmission mode to send a packet to the channel. When channel quality is poor, the transceiver should use a low-rate and conservative modulation mode to reduce the packet drop rate, while when the channel quality gets better, the transceiver should increase the rate to improve the throughput. Unlike cellular V2X, which monitors the channel quality and attunes the modulation and coding scheme (MCS) accordingly, 802.11 protocols lack such a control function and leave the LA scheme to users' discretion, for example,

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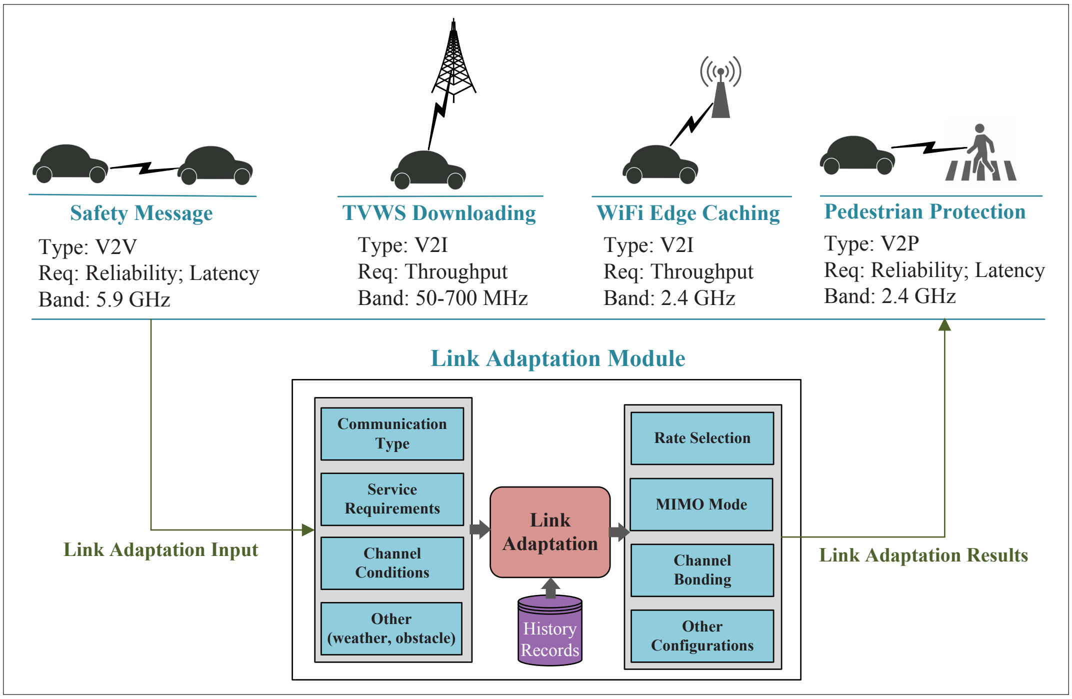

FIGURE 1. 802.11 V2X scenarios.

The original intention of 802.11 LA scheme is to capture the channel variance based on observing the historical frame dropping or measurement results, such as Received Signal Strength Indicator (RSSI) guided rate adjustment. The intelligent LA scheme should consider more network information beyond the channel status, such as cross-layers status, network interworking, etc.

by loading a customized library file to the wireless network driver [8]. In traditional 802.11 products, the LA mechanism in 802.11 relies on recent statistics of the transmission outcome or channel measurements at corresponding rates, including the Auto Rate Fall-back (ARF), SampleRate, and so on. [9]. As 802.11 products are designed mainly for indoor network users, such an LA mechanism is likely to cause inefficient usage of the bandwidth and reduce the network performance. Despite many proposals in LA algorithms against various types of channel dynamics in the past years, an efficient LA scheme for 802.11 radio technologies applied in vehicular communication is lacking, which is diffrent from traditional 802.11 networks in many aspects. First, vehicles move very fast, causing highly dynamic wireless channels. Second, there are many different types of communication peers, including vehicle-to-pedestrian (V2P), V2V, V2I, and so on, whose data transmissions are quite different. Furthermore, strict quality of service (QoS) is demanded by various vehicular applications (e.g., stringent delay guarantee for safety message delivery). All of these special requirements are urging 802.11 V2X to better track channel variance and enhance bandwidth utilization.

Except for the physical channel fading, the efficiency of the 802.11 V2X LA algorithm is also determined by many other factors, such as packet collision due to concurrent transmission, hidden terminals, and NLoS/LoS conditions, which would be even more complicated in highly mobile scenarios. As the 802.11 protocols evolve rapidly, the LA scheme should not only determine a proper medium access control (MAC) layer rate, but also the multiple-input multiple-output (MIMO) mode (e.g., single/double stream, SS, DS) and channel bonding (20/40 MHz) parameters. Such complexity is far beyond the ability of current algorithms, including both sampling approaches and measurement-based methods, which cannot efficiently balance the choice between fast channel following and bandwidth utilization [9], and thus slow down the practical use and standardization of a unified 802.11 LA mechanism.

A data-driven approach provides an opportunity to take into account all impacting factors and provide a timely response to the varying of the transmission environment [10]. Intelligent data tools, such as reinforcement learning (RL), could help to capture both the long-term channel characteristics and the transmission fluctuation in the short run [2]. In this article, we study the requirements for an intelligent LA scheme for 802.11 V2X, and propose a data-driven learning-based architecture for 802.11 V2X wireless transmission. We also set up a reference model to show the throughput improvement by mining the underlying channel pattern in drive-thru Internet. Finally, we identify the opportunities and challenges for the research and development of the intelligent 802.11 V2X LA mechanism.

802.11 V2X LA Requirements

The LA scheme adopted in current 802.11 V2X protocols needs to adapt to multi-dimensional information, including both the external and internal environments and the QoS of various vehicular applications. The application scenarios of such an intelligent LA scheme are shown in Fig. 1, including multi-band transmission, different V2X types and mobility patterns, QoS, and so on. The detailed requirements are summarized in the following subsections.

Network Awareness

The original intention of an 802.11 LA scheme is to capture the channel variance based on observing the historical frame dropping or measurement results, such as received signal strength indicator (RSSI) guided rate adjustment. An intelligent LA

Different network protocol versions might have some difference as the transceiver vendor may upgrade the firmware/software during the whole product life cycle. Understanding the updated features of the protocol software can help an LA scheme better utilize the protocol functions and hardware capabilities such as computing and storage capability, and circumvent hardware imperfections.

scheme should consider more network information beyond the channel status, including cross-layers status, network interworking, and so on.

Physical Channel Status: The physical channel changes rapidly in vehicular networks. The LA scheme should be aware of different channel patterns and the channel variance, such as the RSSI trend between a moving vehicle and a static roadside AP, and the channel between two adjacent vehicles driving in the same direction, which would have widely different fading types. Other parameters include the LoS/NLoS condition, the effect of small-scale fading (e.g., due to multi-path reflection of the road condition), shadowing (due to obstructing objects), path loss, and so on. The physical layer channel information can be obtained from self RSSI or channel state information (CSI) measurement/prediction and also information from external entities.

MAC Layer Network Behavior: In an 802.11 network, transmission failure is caused not only by channel error, but also by collision when multiple users transmit simultaneously[1] [11]. Reducing the packet rate can cause longer transmission time, which could possibly lead to more collisions. Thus, when using the transmission history to predict the channel variance, the LA scheme should be able to distinguish the actual reason and differentiate the channel error from all transmission failures. The LA scheme should also be aware of other MAC layer parameters, such as back-off stage/window size, frame aggregation, and group acknowledgment (ACK), which would have great influence on the result of a transmission attempt.

Network Interworking: Connected vehicles often have multiple access radio technologies, which can work together to provide better network performance. For instance, different 802.11 V2X radios, such as 802.11p and 802.11af devices transmitting in different bands, can work together to aggregate the throughput of different data pipes. Besides, the interworking between the 802.11 V2X and cellular networks can overcome the shortcoming of each other (e.g., to extend the coverage area for vehicle users and reduce the communication cost via traffic offloading diagram) [12]. The LA scheme should utilize such network resources in obtaining channel status, transmission assistance, and so on.

Transceiver Status Perception

The wireless transmission not only depends on the external environment, but also the inner status of the transceiver. The LA scheme should be aware of the transceiver model and make full use of the hardware resources and protocol utilities.

Protocol-Specific: Different network protocol versions might have some difference as the transceiver vendor may upgrade the firmware/software during the whole product life cycle. Understanding the updated features of the protocol software can help an LA scheme better utilize the protocol functions and hardware capabilities such as computing and storage capability, and circumvent hardware imperfections.

Device Snapshot: An efficient LA strategy should monitor the instant status of the transceiver device, such as the transmission queue buffer (would drop packets if all buffer space is exhausted), radio power, CPU load, available backhaul bandwidth, and antenna gain. Besides, an LA scheme should also consider the wireless configuration such as the applied MIMO mode (DS or SS), or if channel bonding is enabled. Such information, combined with historical device status, can help the LA scheme determine the optimal rate/mode among all available settings.

QoS Orientation

Automotive applications require quite different communication QoS. Delay-sensitive tasks such as safety message sharing among vehicles require high reliability and low delay transmission rather than high data rate, while some delay-tolerant applications might require exhausting the bandwidth to achieve higher data rates. The LA scheme should be able to make different policy for packets with different QoS requirements, for example, reduce the link rate when sending safety packets, while risking frame loss to try higher rates to seek larger throughput. For data packets from the backhaul network, the LA scheme is required to identify and map the corresponding packet transmission priority to the QoS of the wireless transmission and choose the proper rate selection policy.

Automotive Context and Peripheral Condition Detection

The automotive context is one of the main factors to shape the communication pattern [13]. The relative velocity/position between the transmitter and the receiver largely determines the Doppler and fast fading effect. For example, in drive-thru Internet, the LA scheme should be able to predict that the WiFi signal strength rises when the vehicle approaches the AP and decreases when the vehicle drives away. In a vehicle platoon situation, the V2V channel between platoon members is likely to be stable. Besides, in a highly dense area such as a road intersection, the communication channel is more congested than in a sparse area. The LA scheme should be able to detect and adapt to such communication patterns and other peripheral conditions (location, weather, etc.).

Performance Focus

To efficiently utilize the available bandwidth resource and achieve better QoS satisfaction for different kinds of data tasks, the LA scheme should rapidly respond to the changing environment and provide packet-level rate/mode adjustment within 802.11 V2X channel coherence time. A lightweight LA scheme is preferred as it does not consume much computing and storage resources, which are limited on most network devices.

Data-Driven Intelligent Link Adaptation Architecture

A traditional prediction or measurement-based LA scheme could not observe all the above-mentioned system status, not to mention the difficulty of taking into account all impacting factors, and thus could only be applied in limited scenarios. It seems impossible to design a unified algorithm to apply to all kinds of channel conditions in 802.11 V2X. The success of the machine-learning-based data-driven methods in recent years has offered

[1] Collision happens due to the uncoordinated back-off process of 802.11 DCF, or for other reasons such as the hidden terminal problem.

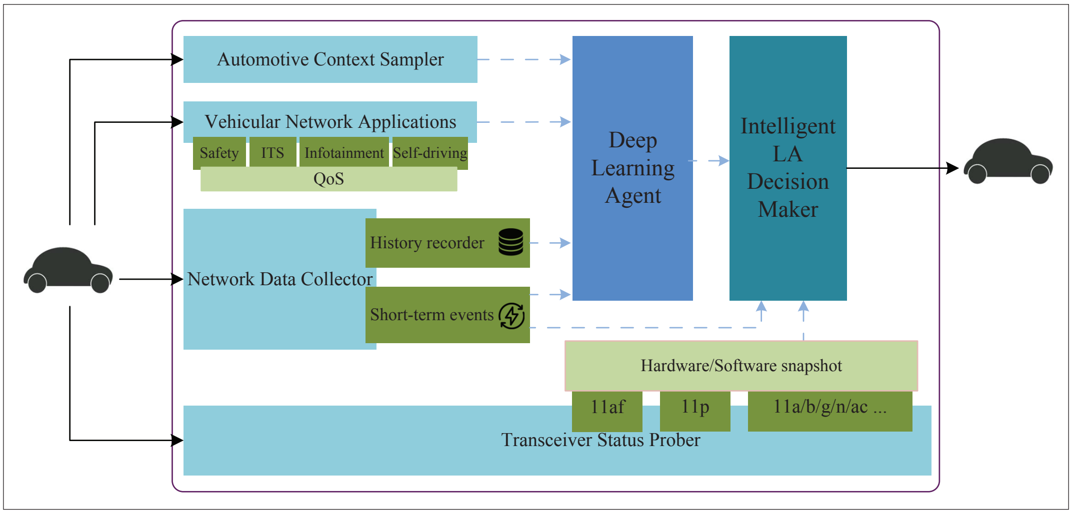

FIGURE 2. Data-driven intelligent LA architecture in 802.11 V2X.

The principle of the data-driven intelligent LA scheme is to capture both the long-term channel characteristics and the short-term fluctuations based on the big data from both external and internal environment, and choose the best transmission rate and mode to fit the vehicular channel and satisfy user's QoS.

the possibility of such intelligent algorithms solving the complicated rate/mode selection problem involving various environment conditions and multiple transceivers with either full or limited observation and transmission history data.

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LA Architecture

The framework of the LA architecture is shown in Fig. 2. The function blocks can be divided into five components, which are explained as follows.

Automotive Context Sampler: The automotive context sampler should observe the vehicular conditions that would affect the wireless transmission, including the number of neighboring users that would contend for the communication channel, vehicle velocity, location, peer relation, weather, and so on. The sampler should also report the packet-level QoS for each application, such as delay-sensitive or tolerant and high throughput orientation, which would lead to different rate selection policies.

Network Data Collector: Network data comprises long-term history data and short-term events. Long-term history can be from its own transmission records and also from the channel measurements of others.[2] Short-term events can be recent packet transmission results or other network events that would alter the transmission condition, such as network topology change, transmission collision, and hidden terminal detection.

Transceiver Status Prober: Both the software and hardware status of the transceiver should be considered. Software information includes the wireless driver version, network protocol stack and other specifications, such as source patches and bug fixes. Hardware information includes the transmit queue buffer space, antenna configuration, radio power parameter, and so on. The LA scheme should be aware of these statuses and make the optimal rate and mode selection.

Deep Learning Agent: The environment conditions captured by the above components will input to the deep learning agent, which would first classify the scenarios into different communication patterns, such as the drive-thru Internet transmission, data transmission among platoon members, and V2V safety message dissemination. For a specific pattern, the agent would learn the relationship between the channel condition and achievable rate/mode from the long-term history data and the feedback of recent transmissions.

Intelligent LA Decision Maker: The final rate/mode decision is made by evaluating the learning result and short-term events (e.g., the feedback of a series of the recent decisions before they are trained in the learning model). The LA outputs are directly applied to the transceiver via the interface provide by the wireless driver.

Feasibility Analysis

To apply the data-driven learning-based LA scheme in practice, it should work compatibly with current 802.11 V2X platforms, which may have very different configurations and specifications. The feasibility of the proposed LA architecture in vehicular conditions is analyzed as follows.

Information Source: Multi-dimensional information can be obtained from various sources for the LA scheme. The local transmission records have already been utilized by many traditional LA schemes to predict the channel quality, which can be obtained by tracking the transmission result of each packet[3] The LA scheme can also acquire the records of his/her brethren in other vehicles via the V2V sharing or download from a data server.[4] Besides, commodity WiFi devices are able to provide a precise power delay profile by collecting the CSI information of the received frames to evaluate the channel signal-to-noise-ratio (SNR) [14]. The onboard units equipped on modern cars can provide automotive status such as velocity and location, together with the surrounding infrastructure information, with which the LA scheme can efficiently detect the communication scenario and capture the transmission pattern. The LA model learned by an LA agent can be shared to other vehicles that pass a similar road section with a similar communication configuration. Such big data in vehicular conditions and the versatile data acqui-

[2] Such as the RSSI measurements obtained from other vehicles.

[3] For example, check if the ACK frame is received.

[4] Such as the roadside edge caching server or Internet database.

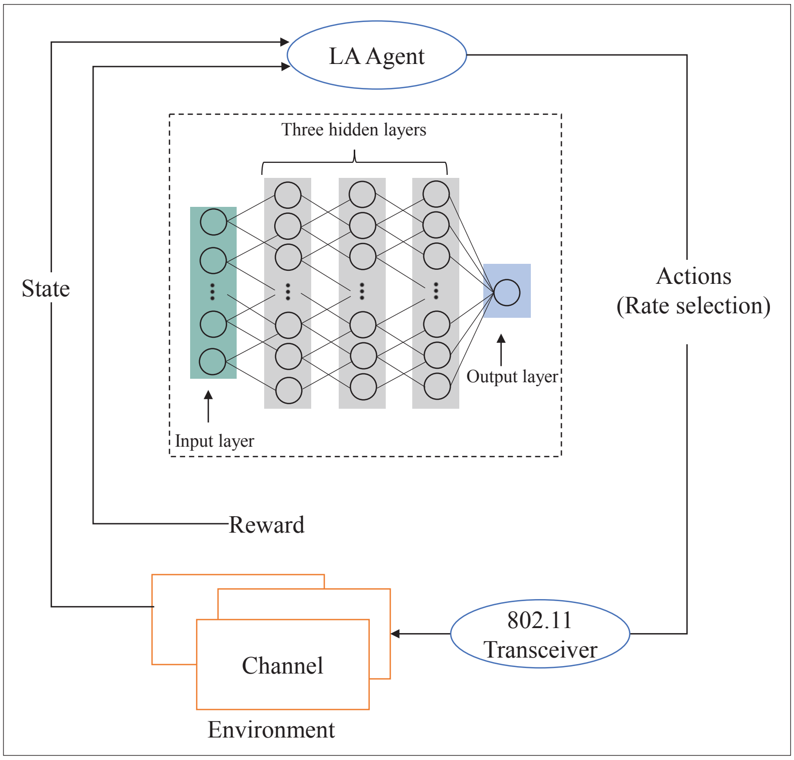

FIGURE 3. Deep learning model for LA in drive-thru Internet.

sition methods can help the LA scheme to better predict the channel variance and make the proper LA action.

Computing Resource: With the development of the semiconductor industry, the processing capability of network devices has grown quickly, which could help reduce the time to perform the machine learning process and provision the packet-level rate/mode selection based on quick calculation of the learned model output.[5] The reduced cost of the storage devices could also help keep more transmission statistics and other information, and thus help build a better and more precise channel model.

Device Compatibility: Most of the 802.11 software has left the choice of the LA scheme to vendors or customers, and thus a new LA scheme can easily be ported to the current software of the network device [9]. The core function of the machine learning process can run on a normal computing platform, and many embedded systems are devised with neural network units that could accelerate the learning process, which would help to accomplish the computation tasks of the learning output in milliseconds, and thus facilitate the application of the proposed LA scheme. Since the LA scheme only adjusts the packet rate and mode of the transceiver itself, and does not affect the transmission of others, it can work with traditional LA schemes running on other devices.

[5] A typical model calculation involves thousands of addition and multiplication operations.

[6] Obtained by assuming the RL always selects the best rate, that is, the maximum rate that could be received successfully.

Reference Model: Data-Driven Learning-Based LA for Drive-Thru Internet

To show the effectiveness of the data-driven learning-based LA scheme, we set up a reference model in drive-thru Internet, where a vehicle communicates with the roadside AP to download/upload data traffic when it moves across the coverage area. We compared the proposed LA scheme with several other methods and show its advantages.

Model Setup

The received signal strength is plotted by a 2D channel simulator considering both the multipath fading and shadowing as the vehicle crosses the roadside network at velocity of 60 km/h [15], whose parameters are listed in Table 1. A snapshot of the simulated channel status is shown in Fig. 4a, which show that the SNR level first increases when the vehicle moves closer to the AP and decreases while the vehicle leaves. We use a neural network including three hidden fully connected layers to learn the underlying pattern in the channel variance, as shown in Fig. 3.

100 channel samples are generated by simulating the drive-thru Internet communication environment, where 50 samples are used to train the learning model and the remaining 50 are used to test the LA performance. We use the latest 20 SNR records in a sample as the input to the neural agent to select a rate, and design a reward function to train the rate selection process and maximize the long-term gain function, that is, the overall throughput that the vehicle can transmit with the AP. Specifically, a random sample is selected as the channel condition in the environment, and the reward function is set to 0 if transmission fails, or to the applied link rate if transmission is successful. The agent would repeatedly adjust the rate selection in all environment conditions to gain corresponding experience for a certain time. The performance of the trained rate selection is compared to other strategies.

Performance Evaluation

Figure 4b shows the comparison between the learning-based LA scheme and other settings. It is shown that the traditional ARF algorithm cannot capture the quick variance of the vehicular channel and can only achieve 25 percent of the optimal throughput,[6] even worse than the random rate selection and fixed rate selection methods. The learning-based LA scheme achieves much better performance of almost 83 percent of the optimal throughput, which validates the effectiveness of the learning-based LA method.

Opportunities and Challenges

An efficient LA scheme provides numerous opportunities for industry, academia, and standardization organizations. It can improve the competitiveness of 802.11 V2X with other communication technologies, especially the cellular-based V2X, that have a full control panel for communication resource management. Manufacturers and vendors will benefit from such improvement and reach higher market share. Besides, efficient LA scheme can expand the application of the high-performance and continuously evolving WiFi devices in vehicular conditions, which are designed mainly for low-mobility scenarios. The proposed reference model provides confidence for the research and development of an intelli-

Parameters	Value
Protocol	802.11n (20 MHz)
Frequency	5.5 GHz (Chan 110)
AP power	20 dBm
Noise level	–90 dBm
Path loss exponent	3
Path loss constant	–12.89 dB
Shadowing power	10 dB
Shadowing decorrelation distance	2 m
Multi-path decorrelation distance	0.05 m
Rician fading parameter *K*	10

TABLE 1. Parameters for the drive-thru Internet.

gent LA scheme for 802.11 V2X, including various automotive communication scenario categorizations, machine learning algorithms, and so on. Due to its strong adaptation to the changing environment and its learning nature, it is promising to design a unified framework to support smart LA in multiple platforms, and thus there is a great opportunity to advocate standardization of the LA scheme for 802.11 products, which has never been fulfilled before.

However, it is difficult to identify all V2X communication scenarios, and the highly mobile nature of vehicle users also poses challenges to differentiate the boundaries of both the spacial and temporal domains. The learning-based mechanism requires repeated experimentation and adjustment to achieve acceptable performance, as there is no explicit theoretical guidance for the underlying channel pattern, which is hidden in neural networks. To design an efficient LA scheme that not only achieves superior performance but also can run in various embedded systems, great efforts should be put into algorithm development and software/hardware porting. In addition, to promote the standardization, it is required to conduct compatibility tests; also, a unified framework should be agreed by network users, vendors, standardization organizations, and other stakeholders.

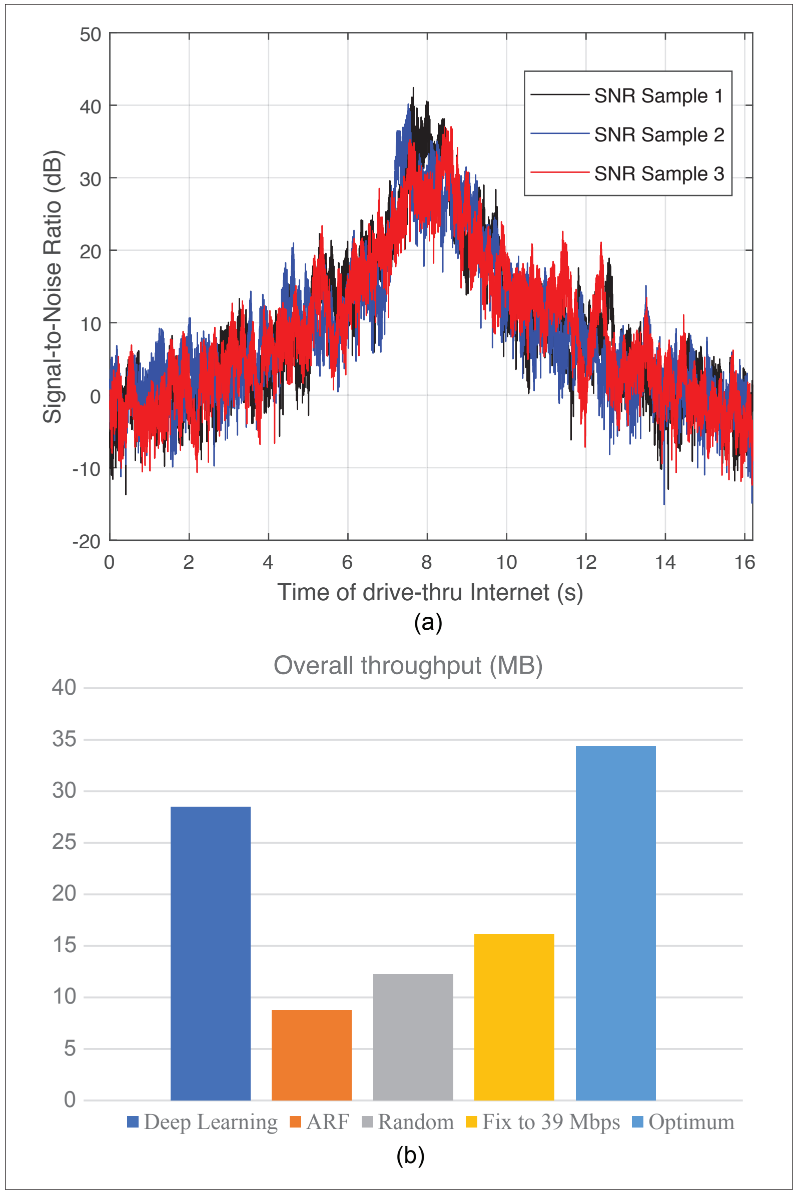

FIGURE 4. Data-driven learning-based LA in drive-thru Internet: a) drive-thru Internet channel snapshot; b) deep learning model-based LA performance.

CONCLUSION

In this article, we have reviewed the requirements of the LA scheme in 802.11 V2X, and proposed a learning-based data-driven architecture to mine the long-term regularity and short-term variance in the vehicular communication environment. We have established a reference model to show that the learning-based model has great potential to deal with the complexity of an efficient LA scheme. We have also discussed the opportunities and challenges of the research and development of such an intelligent LA scheme, and envisioned the standardization of a unified LA framework that can be applied in various V2X platforms.

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