Spatial Intelligence toward Trustworthy Vehicular IoT

Celimuge Wu, Zhi Liu, Di Zhang, Tsutomu Yoshinaga, and Yusheng Ji

Spatial challenges for the vehicular Internet of Things come from mobility, high density, sparse connectivity, and heterogeneity. In this article, the authors propose two techniques, namely decentralized moving edge and multi-tier multi-access edge clustering, to handle these challenges.

Abstract

Spatial challenges for the vehicular Internet of Things come from mobility, high density, sparse connectivity, and heterogeneity. In this article, we propose two techniques, namely decentralized moving edge and multi-tier multi-access edge clustering, to handle these challenges. The "vehicle as an edge" concept of the decentralized moving edge provides a more suitable solution to meet the throughput and latency performance requirements by conducting distributed communication, data caching, and computing tasks at vehicles. Multi-tier multi-access edge clustering generates different levels of clusters for more efficient integration of different types of access technologies including licensed/unlicensed long-range low-throughput communications and unlicensed short-range high-throughput communications. We employ fuzzy logic to jointly consider multiple inherently contradictory metrics and use Q-learning to achieve a self-evolving capability. Realistic computer simulations are conducted to show the advantage of the proposed protocols over alternatives, and several open research problems are discussed.

Introduction

The Internet of Things (IoT) has been recognized as a new mega-trend due to its capacity for bridging the digital world and our real world. The vehicular IoT [1], a combination of the IoT and connected vehicle technologies, could embrace new applications in various fields, including smart transportation, smart cities, smart homes, smart grids, and so on. These applications critically require a *trustworthy* networking architecture capable of *providing more reliable and efficient communications in various network environments*. For emerging vehicular IoT applications, especially performance-sensitive and mission-critical applications such as autonomous driving that require decentralized communications between vehicles, a more *intelligent* networking architecture, specifically an architecture that can *handle the uncertainty, complexity, and dynamic features of the network environment*, is an urgent need.

The main challenge in enforcing a trustworthy vehicular IoT is the spatial diversity of the entities involved in the communications, including the mobility of the nodes, the large number of devices, and the limitations of propagation devices and other resources. This article studies issues for improving the intelligence of the IoT regarding challenges in the space domain. In order to build a trustworthy IoT infrastructure that can deal with a wide range of challenges such as high mobility of nodes, sparse connectivity due to failures caused by disasters or other unexpected events, and the high density of devices and heterogeneity of communication media, we introduce two novel concepts to the decentralized IoT environment, namely, *decentralized moving edge* and *multi-tier multi-access edge clustering*. The decentralized moving edge introduces a solution for network performance degradation due to vehicle mobility, and multi-tier multi-access edge clustering improves the performance in high-density environments with integration of different communication technologies and hierarchical clustering.

There have been numerous works studying the efficient use of IEEE 802.11p in vehicular ad hoc networks [2, 3]. They mainly discuss route selection from the source to the destination and do not consider how to improve network performance with integration of different communication technologies and content caching. Mobile edge computing (MEC) is a key technology for achieving short delay and high throughput. However, mainly focusing on resource allocation in MEC, most studies [4–6] do not sufficiently address how to utilize vehicles as edges and how to select efficient edge nodes.

For sparse connectivity, there are many delay-tolerant networking (DTN) protocols. Recent works cover various aspects of approaches including geo-routing, social relationship-aware routing, and probabilistic routing [7, 8]. However, none of these works discuss how to find an efficient forward node in an anycast scenario, which is one of the main sensor data collection patterns in sparsely connected networks. For high-density challenges, clustering is a well-known way to solve the medium access control (MAC) layer collision problem [9]. Although some studies [10, 11] have discussed the integration of using licensed and unlicensed spectrums, there is no work addressing efficient hierarchical clustering in a multi-access environment.

We tackle the spatial challenges from two perspectives, specifically. mobility and high-density. The decentralized moving edge and multi-tier multi-access edge clustering are proposed to efficiently solve these two challenges. The decen-

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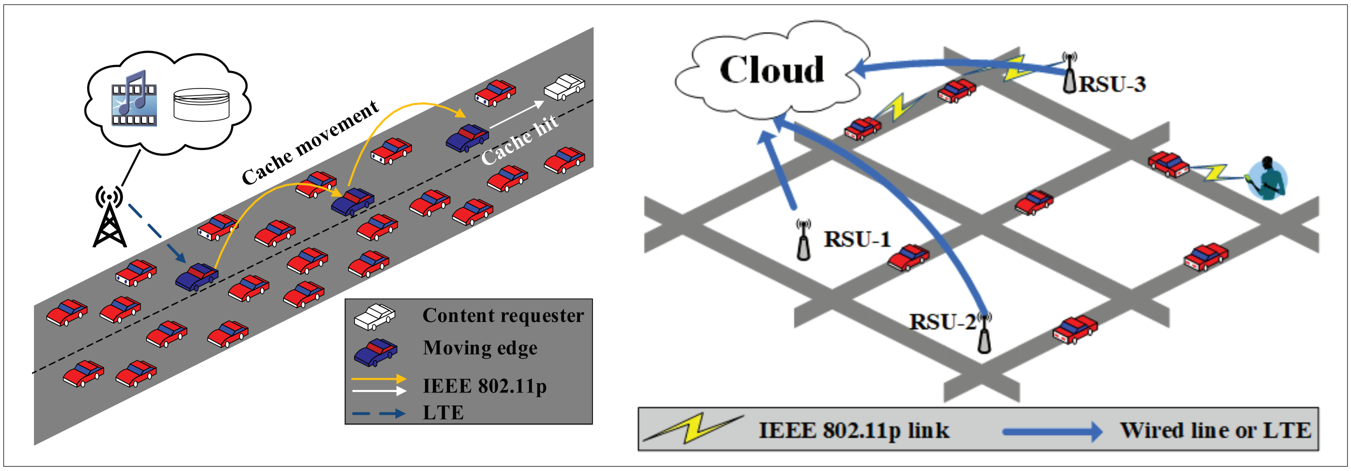

Figure 1. Decentralized moving edge (left: well-connected network, right: sparse network).

tralized moving edge focuses on conducting computing and data caching near the vehicles, and multi-tier multi-access edge clustering utilizes hierarchical clustering to make the communications between vehicles more efficient. The two technologies can be used individually or in combination. An approach combining fuzzy logic and Q-learning [3] is also proposed to integrate with these technologies to achieve intelligence.

The remainder of this article is organized as follows. We describe our solutions for the spatial challenges in the following sections. Simulation results are then presented. Finally, we point out research problems and then draw our conclusions.[1]

Solutions for Spatial Intelligence

To build a trustworthy vehicular IoT infrastructure, we need to consider some major environmental challenges that come from node mobility, sparse connectivity, and the highly dense distribution of nodes/users. We discuss the problems of how to efficiently provide trustworthy computing and communication infrastructure in these challenging environments. For the first challenge, node mobility and sparse connectivity, we propose an approach called the decentralized moving edge architecture that utilizes mobile nodes as an edge to provide efficient communications, data caching, data store-carry-forward, and computing in the vicinity of end users through decentralized communications between edges and users. For the second challenge, the highly dense distribution of nodes, we propose a multi-tier multi-access edge computing framework that generates different levels of clusters for more efficient integration of different types of access technologies including licensed/unlicensed long-range low-throughput communications and unlicensed short-range large-throughput communications.

Decentralized Moving Edge

MEC, which provides an information service environment and computing capability at the edge of the network, can be a suitable solution to meet the throughput and latency performance requirements. How to provide a trustworthy framework for all kinds of applications and efficiently perform edge computing in highly dynamic mobile environments are still open research problems. The inherent major research issue is how to find the best edge node in a decentralized IoT environment. A decentralized moving edge denotes the concept of using vehicles as network edges in order to collect/disseminate information from/to the vicinities using decentralized communications and to conduct computation tasks without totally depending on the cloud.

With the emergence of various vehicle-to-everything (V2X) applications, such as autonomous driving, car camera data collection, real-time traffic information updates, and three-dimensional map data downloading, a new networking architecture that can provide ultra-low end-to-end delay and large throughput is highly required. MEC can be used for conducting computational tasks, caching contents, and efficient routing. By performing these tasks in the vicinity of vehicles, the network performance can be significantly improved, especially in a highly dense network. In the conventional edge computing framework, the nearest edge from the vehicles is a base station. Due to vehicle mobility, the communication between base stations and vehicles could be degraded, and therefore, the approach of performing the edge computing tasks in the base stations (or further distance) is not a satisfactory solution for delay-sensitive applications.

Decentralized moving edge technology can also be used to utilize the mobility of vehicles to perform efficient data forwarding in sparsely connected decentralized networks. It is unpractical to collect all sensor data through the cellular networks due to the bandwidth limitation as well as the cost. In addition, in a post-disaster case, cellular communications could be unavailable. The most promising technology is the decentralized IoT technology, which provides autonomous communications in unlicensed spectrums. However, the problem of widely used unlicensed wireless communications (including WiFi) is their limited transmission range, which poses a networking challenge, namely, sparse connectivity. Here, we focus on delay-tolerant networking (DTN) approaches for vehicle-to-cloud communications that are usually used for vehicle-assisted data exchange. As shown in Fig. 1b, there are multiple interconnected roadside units (RSUs) that perform as gateways to the cloud. A sensor node can be connected to the cloud with any

[1] We use the words "vehicle" and "node" interchangeably in the rest of this article.

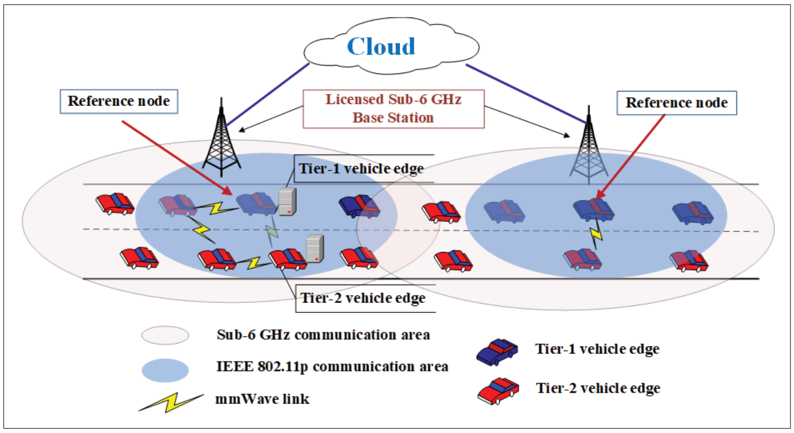

Figure 2. Multi-tier multi-access edge clustering ("communication area" denotes the communication area of the corresponding reference node).

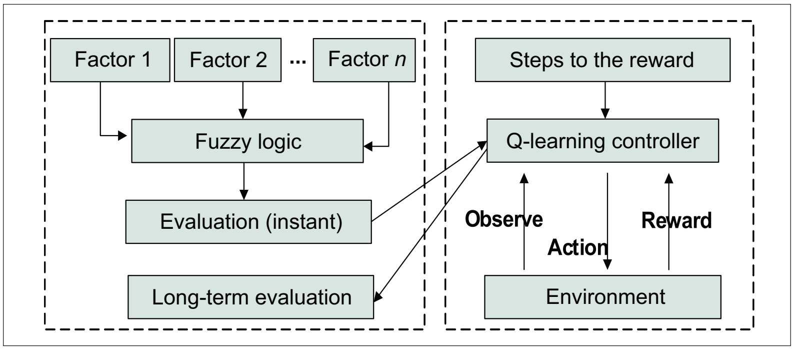

Figure 3. Intelligence with fuzzy logic and Q-learning (for a multi-hop route selection algorithm, "Factor 1," "factor 2," and "factor 3" are the available bandwidth, mobility, and link quality factors, respectively; the instant evaluation is the link state estimation for each wireless link, and the "steps to the reward" will be the number of hops to the destination [3]).

RSU. The networking problem can be defined as DTN anycast since the routing protocol must take into account the joint forwarding performance by multiple RSUs. For this kind of scenarios, the conventional DTN approaches fail to achieve satisfactory performance because: the DTN anycast routing problem is not sufficiently addressed; and the multi-hop data delivery probability is not adequately considered.

Multi-Tier Multi-Access Edge Clustering

The existing wireless technologies show their incompetence in networking performance due to the following facts. First, the vehicles could be deployed in a highly dense manner in some conditions such as traffic congestion. Second, for rural areas, the existing approaches are not able to support a large amount of concurrent traffic. In cellular networks, network performance drops drastically along with the increase in the number of users. Fortunately, MEC provides a way to satisfy this need by conducting the computational tasks and data caching near the end users. In this regard, we propose a multi-tier multi-access edge clustering architecture integrating multiple types of wireless communication technologies.

We first introduce an MEC architecture based on the concept of "user device as an edge." The proposed architecture utilizes the computational capability of devices and then creates multi-tier edge clusters. We propose a cluster-based approach that integrates licensed sub-6 GHz band, large-throughput short-range communications, such as millimeter-wave (mmWave) and IEEE 802.11ac, and long-range low-throughput communications (IEEE 802.11p, IEEE 802.11ah, SIGFOX, LoRa) for multi-access edge computing in a heterogeneous IoT.

As shown in Fig. 2, three different types of communications, namely, cellular communications, mmWave, and IEEE 802.11p, are used for data delivery [12]. We define two different types of user edges: tier-1 and tier-2. Whereas tier-1 edges are directly connected with sub-6 GHz base stations, tier-2 edges have to connect to tier-1 edges with mmWave or IEEE 802.11p in order to access sub-6 GHz base stations. Tier-1 edges are used to conduct content caching, data aggregation, and computation (e.g., video analysis). With data caching and data aggregation at the Tier-1 edges, we can achieve more efficient use of wireless spectrum and short delay. A user device works as either a tier-1 or tier-2 edge depending on the surrounding environment, including network node distributions and available wireless resources.

Intelligence with Fuzzy Logic and Q-Learning

An intelligent protocol for vehicular networks should satisfy the following two requirements. First, the protocol should be able to achieve a good decision with inaccurate information in an uncertain and complex environment as the information maintained at each vehicle is erroneous. Second, the protocol should be capable of self-evolution with the change in communication environment. The factors that determine communication performance, including link quality, inter-vehicle distance, vehicle distribution, and vehicle density, are possibly contradictory and change frequently, resulting in difficulty with using simple mathematics to formulate a performance optimization problem. For example, for a multi-hop routing problem, the inter-vehicle distance, link quality, and mobility should be considered jointly. Since fuzzy logic allows imprecise or contradictory inputs, we introduce a fuzzy-logic-based approach to jointly consider multiple factors in order to handle imprecise and uncertain network environments. A fuzzy system is easy to design, flexible, and tunable by changing the fuzzy rules and membership functions. As shown in Fig. 3, multiple metrics can be combined through a fuzzy logic algorithm, and then a final evaluation value can be generated with good accuracy and low complexity. Q-learning is used to judge whether a decision is correct or not by using a model-free approach, ensuring the self-evolving capability of the protocol. By using Q-learning, a system can maximize its long-term outcome based on the reward from the environment. The proposed approach does not incur high computational complexity as the Q-table update is a simple mix of multiplication and addition, and the fuzzy logic algorithm uses simple membership functions. The proposed approach is easy to implement in real devices as it does not require modification of lower layers such as the MAC and physical layer.

For the decentralized moving edge in fully connected networks (Fig. 1a), we design a context-aware vehicle edge node selection algorithm where the vehicle density, vehicle distributions, potential communication traffic pattern, and signal qualities between V2V communications are jointly considered by a fuzzy logic algorithm. In contrast, in a sparse network (Fig. 1b), we propose a protocol that takes into account the multihop multi-destination encounter probability by using a Q-learning algorithm. The Q-learning algorithm is modeled as follows. The entire network is defined as the environment, and each network node is a learning agent. The action at each agent is to find the next forwarder node. Therefore, the possible actions allowed at each agent are taken by the nodes that encounter the current agent. Each agent exchanges information with the nodes that are encountered in order to find the best forwarder node. A Q-Table is maintained at each node where each *Q*-value [$Q(D, m)$] shows the appropriateness of using *m* as the next replicator for a packet bound for a destination (*D*). In order to take into account the anycast encounter probability, we propose the concept of "virtual gateway (V-GW)," where multiple RSUs are considered as the same virtual gateway. A Q-value exists for each pair of a gateway and a possible candidate for packet forwarding. Since the reward is discounted by the hop count, each Q-value for V-GW shows the multihop anycast packet delivery probability of the corresponding node.

For multi-access high-density vehicular networks, a fuzzy-logic-based approach is used to conduct vehicle clustering where cluster head nodes are responsible for providing gateway capabilities between different types of communications. By taking into account the vehicle velocity, network topology, and antenna height for the cluster head selection, we can ensure that the cluster head nodes are reliably connected with each other [12].

Performance Analysis

Well-Connected Scenarios

We used the network simulator ns-2.34 to conduct simulations. The simulation scenario is the same as in [12]. A freeway road that has two lanes in each direction was used. The Nakagami propagation model was integrated to simulate a realistic vehicular communication channel. There were three different types of communications available for vehicles, namely, IEEE 802.11p, mmWave, and Long Term Evolution (LTE). The average IEEE 802.11p transmission range was 250 m. Each vehicle blocks mmWave signals with a probability of 75 percent (this could vary depending on the network topology and antenna height). In the simulations, 15 percent of vehicles have higher antennas than others, and they increase the coverage of mmWave communications by 40 percent.

The proposed protocol was compared to "LTE-only," "random edge (10%)," "random edge (10)," and "greedy edge." "LTE-only" denotes that every node uses LTE for the content distribution (all vehicles perform as edges [gateways]). In "random edge (10%)," 10 percent of vehicles are randomly selected to work as edges, and the others are connected to the edges through mmWave or IEEE 802.11p. Here, edge nodes are used to provide LTE connections to non-edge nodes. In "random edge (10)," the randomly selected 10 vehicles work as edges. In "greedy edge," each vehicle works as an edge or directly connects to an edge with mmWave communications. The number of base stations was 1. The data traffic was from the BS to the vehicles, and all the vehicles were considered as intended receivers. The performance evaluation was conducted for various vehicle densities. In the following figures, the error bars show the 95 percent confidence intervals.

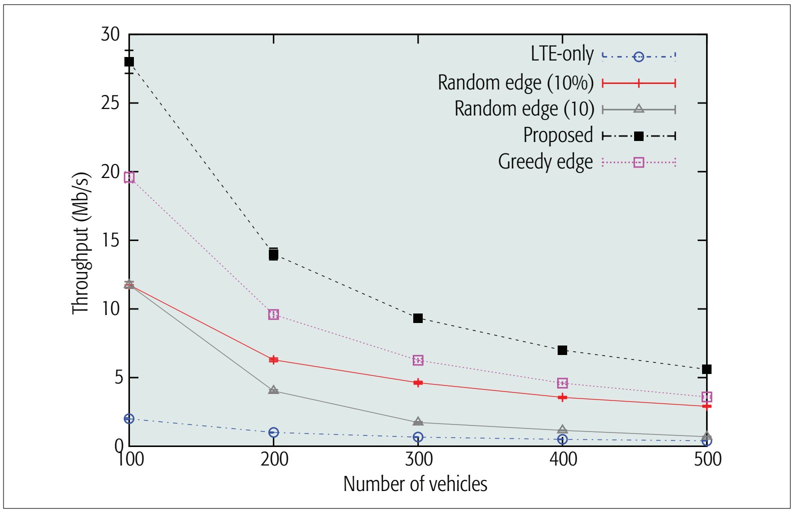

Figure 4. Throughput for various node densities.

Figure 4 is the throughput comparison for various numbers of vehicles. It is clear that when the vehicle density is large, "LTE-only" shows low throughput because the network bandwidth allocated for each node is small. This demonstrates the importance of utilizing multi-access technology. As shown by "random edge (10%)" and "random edge (10)," we can observe that the random selection of edge nodes is not a good approach as there is no guarantee that the selected nodes could connect other non-edge nodes with high-throughput connections. Furthermore, the optimum number for edge nodes is dependent on the node density. "Greedy edge" can achieve better performance by providing all nodes with LTE or mmWave connections. However, "greedy edge" always selects a larger number of edge nodes (Fig. 5), resulting in a decrease in the bandwidth allocated for each edge. Since the proposed protocol takes into account the vehicle velocity, link quality, and vehicle distribution for the edge selection, it shows the best performance. The proposed approach can also achieve a shorter delay by using edge nodes for packet forwarding, reducing the number of concurrent sender nodes as compared to traditional approaches [13].

Sparse Scenarios

We used the ONE simulator [7] to conduct simulations of the default urban scenario in Helsinki. Three RSUs (gateways) were uniformly distributed, and two different types of nodes, namely, vehicles and pedestrians, were used. The pedestrians do not forward messages. The performance evaluation was conducted in different message generation intervals. There were 60 vehicles, and the transmission range was 200 m. The buffer size at each node was 20 MB. The maximum achievable throughputs

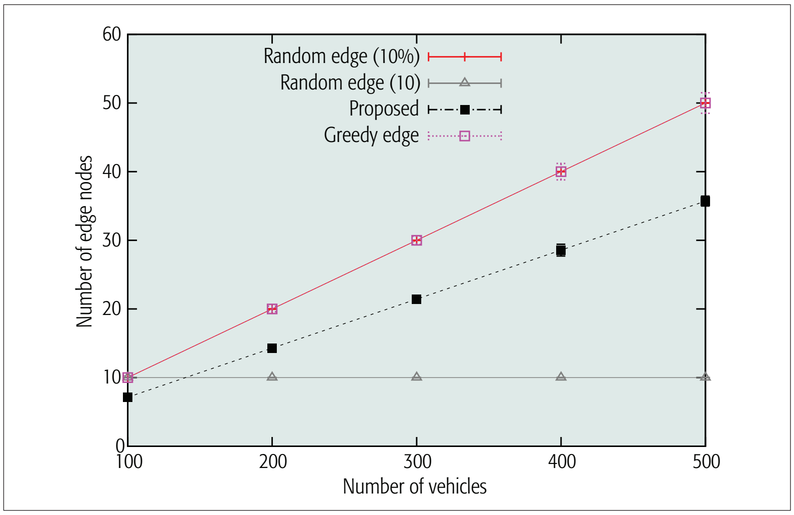

Figure 5. Number of edges for various node densities ("random [10%])" and "greedy edge" overlap).

for vehicle-to-vehicle and vehicle-to-pedestrian links were 6 Mb/s and 2 Mb/s, respectively. We used the default setting of the ONE simulator for other simulation parameters. The proposed protocol was compared to three baseline protocols, namely, epidemic routing, Spray-and-Wait, and a PROPHET-based approach [7].

Figure 6 shows the comparison of end-to-end data delivery ratios under different data traffic rates (message generation intervals). The proposed protocol is able to provide almost a 100 percent delivery ratio. This is because it can evaluate candidate nodes in terms of multi-hop anycast encounter probability by using the Q-learning algorithm, resulting in efficient packet forwarding. "Epidemic" routing performs poorly due to blind replication. Although a "PROPHET-based" approach compares the destination encounter probabilities of candidate nodes before data transfer, it fails to provide satisfactory performance since the anycast encounter probability is not addressed. In the case of a high data rate (small message generation interval), "Spray-and-Wait" has poor performance. This is because in "Spray-and-Wait," a data packet is forwarded to a predefined number of nodes (6 by default), and each node maintains a copy before reaching the destination. Therefore, when the traffic rate is high, the data size in the buffer becomes large, which incurs packet drops as a result of buffer overflow. Due to the low message replication overhead and efficient anycast scheme, the proposed protocol can achieve a high packet delivery ratio for different message generation rates. The lower overhead and higher delivery ratio contribute to a shorter delay [14].

Future Research Directions

The spatial challenges open up many exciting and critical future research problems, such as the following.

Protocols with Self-Evolving Capability: Most studies are designed to optimize the network performance in a specific scenario. As a result, the corresponding solution is based on accurate knowledge of the environment and an assumption that it does not change. However, in a decentralized network such as a vehicular network, which is also a main part of 5G networks, the knowledge obtained at each node is imprecise, and the communication parameters change with time (e.g., the time-varying channel of V2X). Therefore, the networking protocols should be able to evolve in response to a change in the environment. Online learning algorithms, such as reinforcement learning, will continue to be one of the main ways to achieve self-evolution.

Learning in Fast-Changing Environments: A trustworthy network requires the protocol to adapt quickly to changes. Specifically, the protocol should be flexible and be able to tune itself when the network topology changes. Typically, learning algorithms require a long time before convergence, which makes the use of conventional learning approaches in vehicular networks particularly challenging. Transfer learning [15] could provide a way to improve the learning speed by exchanging information among agents. Newly arriving nodes can achieve fast learning by utilizing the learned information at the neighbor nodes. The learned knowledge at an agent can be utilized to facilitate learning at another agent, which can accelerate the convergence speed.

Optimization with Neural Networks: Reinforcement learning is able to find the best action to maximize the cumulative reward. However, since the network state is dependent on the user distribution, traffic pattern, QoS requirement, and device capability, the state space is extremely large and complex, resulting in difficulty with explicitly defining the state and action space. Neural networks can be integrated with reinforcement learning to process this complex logic by replacing the conventional value function.

Data-Driven Prediction and Optimization: Currently, we are experiencing explosive data growth for vehicular IoT. The design and management of a vehicular network can benefit from data collected from vehicles, RSUs, user cell phones, and other sources. It is possible to improve the networking performance based on data-driven prediction and optimization. On the other hand, the data can be highly dimensional, distributed, structure-less, and complex. This poses a challenge for the design of an efficient and powerful platform that scales well with data volume, velocity, and variety. The use of the computing capability of vehicles for data analytics would be an interesting topic.

Unified Solution for Different Scenarios: Currently, most protocols are designed for a specific scenario, and a general solution for different topologies is missing. For example, a protocol designed for a high-density network does not work well in a sparsely connected network. A unified solution that can work in various environments and applications is required. This can be achieved by an efficient combination of existing techniques.

Decentralized Trust Management: Trust management is particularly important for delay-sensitive or mission-critical applications, such as autonomous driving and collision avoidance systems, as some fake/wrong messages could possibly incur an accident. Some vehicles barely have good access to the cloud, which incurs a problem in trust management as the trust evaluation should be conducted in a distributed way using decentralized communications between devices. Since there is no centralized controller that can observe the behavior of all the nodes in vehicular networks, it is important to design a multi-agent trust management approach where multiple agents communicate with each other to evaluate an event correctly.

Conclusions

In the paradigm of a vehicular IoT, this article discusses the spatial challenges in terms of mobility, sparse connectivity, and high density, and then describes the corresponding solutions. We introduce two technologies, namely, decentralized moving edge and multi-tier multi-access vehicle clustering. The decentralized moving edge technology is able to improve network performance by conducting data caching, store-carry-forward, and computing at vehicle edges, and multi-tier multi-access edge clustering supports efficient communications in a high-density environment by integrating different communication technologies with hierarchical clustering. We also propose an approach that employs fuzzy logic and reinforcement learning to cope with the uncertainty and dynamic features of vehicular networks. Simulation results show that the proposed technologies achieve better performance than other baseline approaches in various network conditions. Finally, we share some future research directions.

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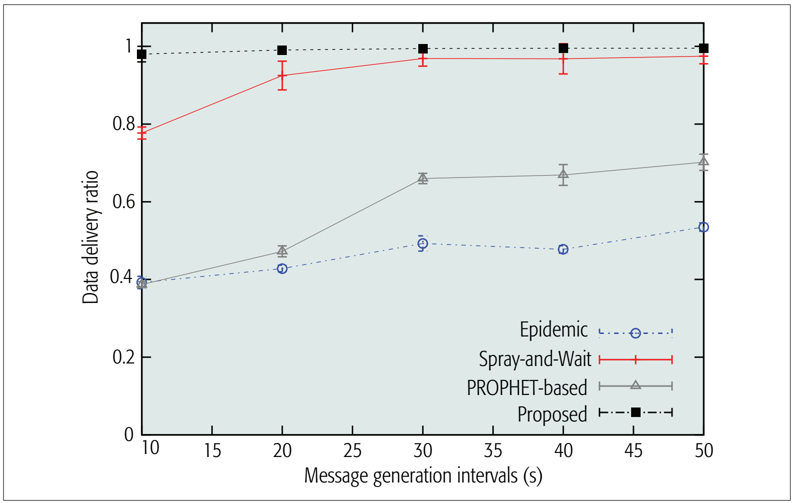

Figure 6. End-to-end data delivery ratio for various message generation intervals.

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