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Cooperative vehicular networks: An optimal and machine learning approach ☆

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ABSTRACT

Intelligent Transport Systems (ITS) provide a promising technology to enhance road safety. The vehicular standard wireless access in vehicular environment (WAVE), also known as dedicated short-range communication (DSRC), can assist in reducing the number of deadly crashes. However, DSRC has a limited range. To enhance the network coverage, roadside units (RSUs) are placed along the road. However, the placement of RSUs at every instant increases the infrastructure cost. In this paper, we proposed the cooperative vehicular architecture, with network function virtualization (NFV) enabled RSU inside the mobile edge computing (MEC) unit. RSUs are only placed in the dense traffic region. We applied the Long short-term memory (LSTM) based machine-learning algorithm to predict the traffic flow based on the vehicle information table (VIT) maintained at the MEC unit. NFV is implemented at the top of RSU. Based on predicted traffic density it assists RSU to enhance its coverage range by exploiting the transmit power. Furthermore, MEC is also responsible for cooperative relay-based communication. Optimal stopping theory is modeled to select the best candidate relay node immediately. In this paper, we tested the proposed scheme in actual on-road vehicles and through simulations performed in network simulator NS-3.

1. Introduction

Future communication applications require a fully integrated network architecture providing support to the advanced technologies. 5G and beyond integrated with intelligent and cutting-edge methodologies serve the purpose while resolving the challenges and constraints in hand [1]. Recent technological innovations lead to tremendous development in communication devices empowering information exchange among elements from cell phones to fast-moving vehicles operating in closed spaces as well as in outdoor environments. Communication undergoes considering the quality of service (QoS) and quality of experience (QoE) to understand the related advantages, for example, low latency, dynamic environment adaptation, high reliability, and so forth [2,3].

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The emerging software-defined networks (SDN), network function virtualization (NFV), and mobile edge computing (MEC) in 5G can improve the internet of vehicles (IoVs) to provide an affordable, efficient vehicular communication system [4,5]. Conventional vehicular systems lack the adaptability of adapting to dynamic changes because of the inflexible nature of the system. The SDN and NFV provide flexibility with MEC providing the distributed computing and offloading capabilities for the vehicular systems. With the inherited programmability feature, the SDN introduces diversity in the internet of vehicles (IoV) over the vehicular cloud. SDN and NFV provide the functionality to the network providers of virtual network elements deployment that enhances efficient resource utilization without additional deployment cost. In this manner, these vehicular cloud networks (VCN) technologies can care take of IoV challenges including limited connectivity options and the non-flexible nature of the infrastructure.

5G enables machine learning integration in the communication system including the vehicular communication system forming an intelligent vehicular network [6]. Artificial intelligence in vehicular networks introduces efficient decision-making with cost-effective resource utilization [7]. Fast data transmission with wide communication bandwidth is provided with additional computational support over remote processing at edge servers over roadside units (RSU). Resources are distributed over different geographical locations, communicate over the backbone network, and operate in an integrated manner.

In this paper cooperative vehicular architecture is proposed. The proposed architecture consists of NFV-enabled RSU inside MEC. Since RSUs are only deployed in dense vehicular regions, the proposed architecture employs the long short-term memory (LSTM) based neural network to predict the future location of vehicles. These future predicted values are utilized by the MEC to enhance the RSU coverage range by exploiting the transmit power of the RSU. Furthermore, MEC also assists vehicles with relay selection in cooperative relay-based communication. The optimal stopping theory is modeled for the selection of relays while consuming minimum time. The main contributions of the paper are as follows.

- The proposed scheme is tested on-road vehicles for selecting the optimal relay candidate. Universal peripheral devices (USRPs)/software-defined radios (SDRs) are programmed for on-road experimentation.
- A stacked-layer LSTM model is proposed and applied at the MEC, to predict the vehicle density. The predicted vehicular density is utilized by the MEC to extend the network coverage.
- NFV layer is devised at the RSU, which supports agile services. NFV assists RSU to adapt their transmit power to enhance the transmitting range based on vehicle density.
- Since time is very critical in vehicular communication, the optimal stopping theory is modeled for the selection of relays. The optimal stopping approach helps to select the best candidate relay node in a very short time.

The rest of the paper is organized as follows. Section 2 presents the related work. The system model is discussed in Section 3. Section 4 and Section 5 present the experiment and simulation based performance evaluation respectively. Finally, the conclusion is drawn in Section 6 and future work is discussed in Section 7.

2. Related work

Cooperative vehicular networks get the attention of the research community as it plays a significant role in guiding vehicles to communicate in adverse channel conditions. In multi-hop V2V communication, data are forwarded from transmitter to receiver via cooperative relays. Resource allocation and relay selection have become challenging tasks in cooperative relay transmissions to improve the overall system performance. In [8], user-centric cooperative communication is proposed. For the selection of cooperative roadside units, a station voting method is presented which determines the cooperative relay value for the selection of the optimal one. The simulation-based study is conducted, however, the practical on-road evaluation is not performed.

In vehicular networks, the timely arrival of message packets is important to notify the drivers regarding safety measures. In [9], a scheme is presented to expedite the data dissemination, the vehicles moving in a direction where the accident has occurred, form a cluster, and collaborate with the vehicles moving in the opposite direction to spread the information fast. In [10], the vehicles communicate with each other using device-to-device (D2D) and notify the traffic server of abnormal events on road. Crowdsensing-based real-time traffic management (CREAM) framework is presented to shorten the response time by cooperative message uploading. In [11], the issue of data delivery is investigated for a hybrid V2I/V2V network. The capacity and delay model which occurs during the data dissemination phase is formulated. Based on the analytical analysis an online cooperative data uploading scheme is proposed which can provide better average uploading throughput and reduce the delay.

Currently, in vehicular network environments, IEEE 802.11p/dedicated short-range communication (DSRC) and cellular 5G are considered primary radio access technologies. But either of them cannot provide low-latency and high-reliability communication. The SDN-based architecture along with MEC is studied [12] to overcome the loopholes of the current vehicular network architecture in terms of latency, reliability, and data rate. In this architecture, the SDN controller helps the vehicle to communicate with other vehicles or infrastructure utilizing DSRC or cellular communication. If the distance between two vehicles exceeds three hops, they will use cellular networks otherwise DSRC protocol will be used.

To process the information intelligently cars need to have sufficient computation capability which most vehicles do not possess. The onboard unit (OBU) of a vehicle has limited computation capability which cannot meet the demand of future vehicular networks. A MEC-based framework is proposed for autonomous vehicular edge (AVE) and hybrid vehicular edge (HVC) [13]. In [14], for cooperative task scheduling, max–min and particle swarm optimization (PSO) algorithms are modified. These algorithms are used to find the best set of service vehicles available which provide enough computation power to execute the task and hence minimize the execution time. Since local delay is the main parameter in mobile edge computing, to reduce the local delay analytical models are proposed in [15] for the investigation. Moreover, to balance the computational load at the MEC, a deep learning-based solution is presented for optimizing the load distribution at the MEC [16].

Network virtualization along with SDN provides the capability to exploit the network parameters. The network parameters such as transmission power could be exploited to cover the white regions. In [17], unmanned aerial vehicle (UAV) assisted VANETs is presented. However, to meet the distinct user requirements in terms of bandwidth and latency, the network is virtualized to fulfill the diverse services. In [18], virtual networks are created with different transmission parameters such as power and modulation coding schemes (MCS) to minimize the interference between two virtual networks. NFV is a promising solution for transforming 5G network slicing into reality. Two key technologies: NFV and SDN are discussed and how they will drive the future 5G networks [19]. For ultra-high-speed and reliable communications resource management is a key factor in vehicular environments. The flow-based policy framework is proposed to improve the overall performance of 5G vehicular networks. Wireless virtualization is utilized to allocate radio channels for V2V communication based on flow classification, i.e., safety-related flow or no-safety-related flows, and the SDN controller manages the flows for V2X communication.

Testing different VANET applications is a daunting task because of the dynamic vehicular network environment which includes unpredicted driver behavior due to rapid topology changes and dynamic node mobility. Network simulators such as ns-2/ns-3 and OMNET++ in association with the urban mobility simulators such as SUMO can simulate complex vehicular scenarios. But real testbed features are missing in those simulators, that is why QoS and QoE cannot be ensured as well as user testing features are not available. Testbed, to validate the performance of any vehicles which comply with the J2945/1 standards in a congested environment, is discussed [20]. A DSRC-based roadside beaconing protocol is studied [21], called BESAFE to facilitate data sharing between RSU and autonomous vehicles. Software architecture is divided into two parts: upper layer application (ULA) and lower layer core (LLC) which gives more flexibility to deploy them in the hardware. Contrary to the previous work, in this paper, we investigate NFV implemented at the top of RSU. NFV assists RSU to vary transmit gain based on predicted traffic density. For prediction deep LSTM based model is implemented at the MEC. In this paper, we also evaluated relay-based communication and performed a real-time on-road evaluation.

3. System model

IEEE WAVE/DSRC is considered to be the most eligible candidate in vehicular communications [22]. However, there are shortcomings in DSRC due to its short coverage range. To overcome this, RSU could be placed to enhance the range of communication for continuous connectivity. Deployment of RSU at every interval would increase the infrastructure cost. Therefore, cooperative vehicular architecture with NFV-enabled RSU inside MEC is proposed as depicted in Fig. 1. It consists of OBUs called vehicles and RSU are placed along with the MEC at only hot regions i.e., densely populated locations where the usual traffic is high. The LSTM-based machine learning algorithm is applied at MEC to predict the vehicle's flow. NFV is implemented at the top of RSU, based on predicted traffic distribution NFV is exploited to enhance the RSU coverage by increasing the transmission power. Moreover, MEC assists vehicles in cooperative relay communication.

The system model consist of vehicles $V = \left\{v_1, v_2, \dots, v_N\right\}$ communicating with each other using 802.11p/WAVE. The vehicles exchange road safety messages. Fig. 2 shows the message frame format. From left to right it consists of header bits, preambles, basic safety messages, traffic information messages, infotainment messages, and a cyclic prefix.

RSUs are only deployed in the dense traffic region to overcome the total cost of infrastructure. For the installation of RSU in densely populated areas traffic models is studied. The Payne–Whitham (PW) model [23] is considered for the traffic flow. This model characterizes the real scenario assuming the driver reaction is based on traffic density. Eq. (1) and Eq. (2) show the PW model for traffic flow.

$$\frac{\Delta\rho}{\Delta t} + \frac{\Delta\rho v}{\Delta x} = 0 \tag{1}$$

$$\frac{\Delta v}{\Delta t} + v\frac{\Delta v}{\Delta x} + \frac{{C_0}^2}{\Delta\rho}\frac{\Delta\rho}{\Delta x} = \frac{\Delta v_e(\rho) - v}{\Delta\tau} \tag{2}$$

Eq. (1) shows the LWR model first proposed by Lighthill, Whitham, and Richards [24] for traffic flow. In Eq. (1), ρ represents the density and v represents the velocity. This model does not accommodate the non-equilibrium flow of traffic [11] such as abrupt changes in velocity. To address this gap, in Eq. (2) the vehicular acceleration is considered. It predicts the forward reaction by the driver. The C_0 is a constant and it varies between 2.4–57 m/s [23]. v_e represents the equilibrium velocity based on density distribution ρ. Based on the LWR traffic model the vehicle density is simulated. Fig. 3 shows the vehicular density.

For the placement of an optimal number of RSUs, the elbow method is utilized. The Elbow method assists to find the optimal number of clusters. The elbow method is applied to the vehicular traffic flow generated in the simulator to find the number of RSUs required to place. Elbow method relies on the distortion function for finding the optimal number K. The distortion function is modeled as shown in Eq. (3). It decreases as the value of K increases. K represents the number of required RSU. The increase in the value of K also increases the cost of deployment. The elbow point shows the value of K, at which the value of distortion declines the most. After the elbow point, the value of distortion remains unchanged or slightly changes. Fig. 4 shows that $K = 3$ optimal number of RSUs that are required. After getting the K number of RSUs, a k-mean algorithm is used to find the best possible dense regions for the deployment of the RSU considering the minimum infrastructure cost.

$$J(c,\mu) = \sum_{i=1}^{m} \left\| x^{(i)} - \mu_{c^i} \right\|^2 \tag{3}$$

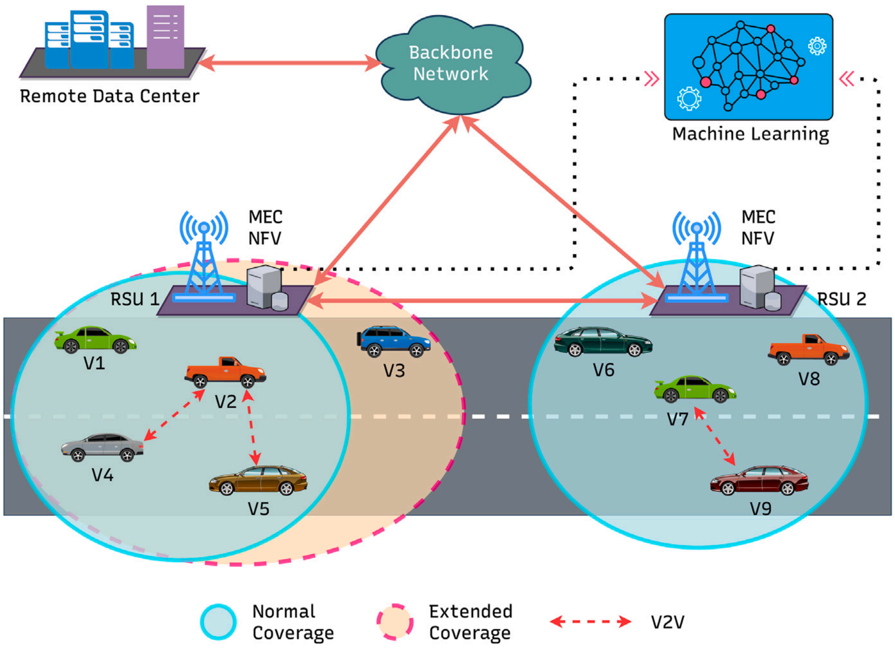

Fig. 1. Cooperative vehicular architecture.

Header Bits	**Preambles**	**Basic Safety Messages**	**Traffic Information Message**	**Infotainment Message**	**Cyclic Prefix**

Fig. 2. Message frame format.

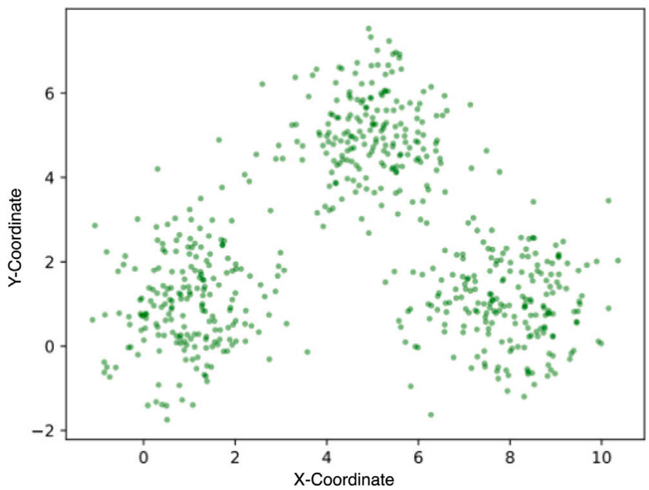

Fig. 3. Vehicle density.

Algorithm 1 shows the K-mean clustering. In step 1, $K = 3$ arbitrary cluster centroids (μ) are selected for the training. The distortion function is modeled for the convergence of an algorithm. In Eq. (3), J represents the sum of squared distances between $x^{(i)}$ and the cluster centroid. The algorithm outputs the optimal position of deployment for the $k = 3$ number of RSUs. Fig. 5 shows the positions of RSUs, and where to be placed. Since, they are deployed only in specific dense regions, however, to provide coverage other than those regions we exploited the following technologies (a) NFV enabled RSU and (b) RSU inside MEC.

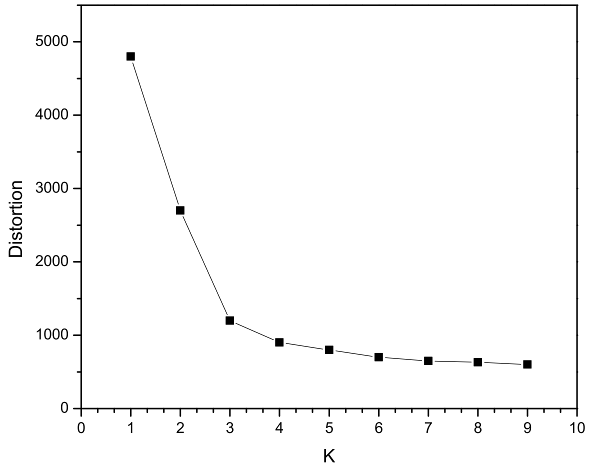

Fig. 4. Elbow curve.

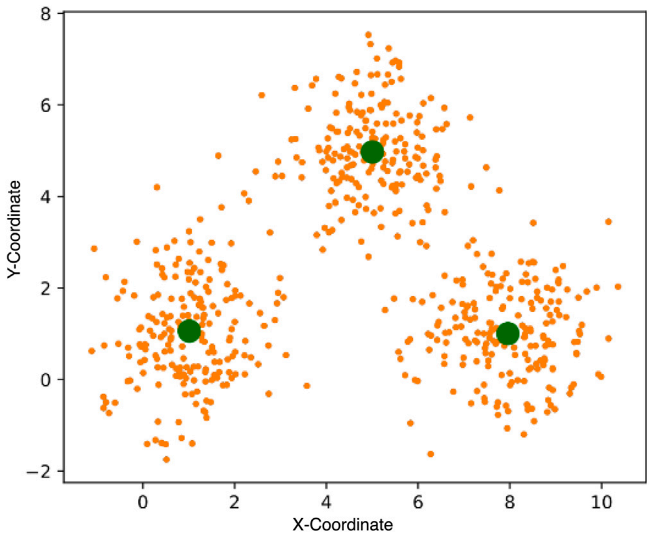

Fig. 5. RSU placed at cluster centroids.

Algorithm 1: Clustering

Step 1: Initialize Cluster Centroids: $\left\{\mu_1, \mu_2, \ldots \mu_k\right\}$

Step 2: Repeat until Convergence

{

For (each i)

$c^i = argmin_j \left\| x^i - u_j \right\|^2$

For (each j)

$u_j = \frac{\sum_{i=1}^{m} \left\{c^i - j\right\} x^i}{\sum_{i=1}^{m} \left\{c^i - j\right\}}$

}

$J(c, \mu) = \sum_{i=1}^{m} \left\| x^{(i)} - \mu_{c^i} \right\|^2$

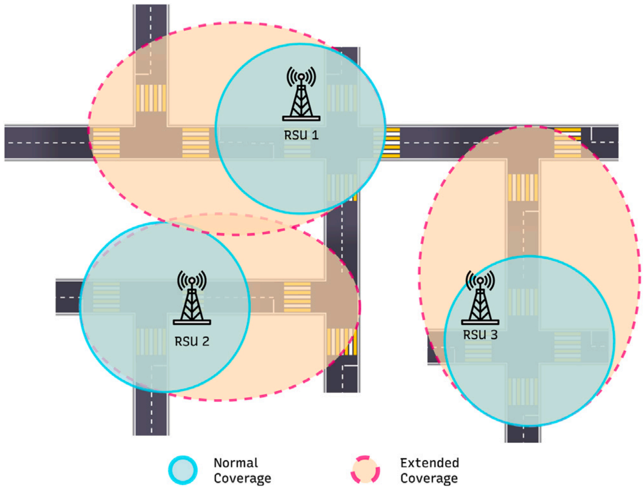

Fig. 6. RSU with extended coverage range.

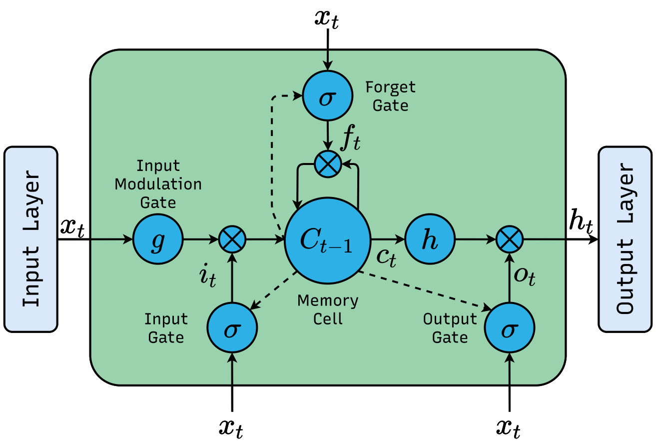

Fig. 7. LSTM cell.

3.1. NFV enabled RSU

NFV benefits in terms of supporting forthcoming technologies in vehicular communications. In this paper, we implemented NFV at the top of RSU, which assists RSU to enhance its transmitting range by varying the transmit power. RSUs are placed at specific locations to reduce infrastructure costs. As can be seen from Fig. 6, RSU has a limited range. If the vehicle's density increases at a certain location that is out of the range of RSU, NFV is capable to assist RSU in increasing the transmitting range by varying the transmit power to cover those regions. A deep learning model based on LSTM is proposed to predict traffic density. RSU collects the vehicle information such as speed, location, and direction. After collecting the information RSU sends the information to the edge. At the edge, the vehicle information table (VIT) is maintained and updated. The proposed LSTM-based algorithm is applied at the edge to predict road traffic based on VIT.

Fig. 7 shows the LSTM cell. The proposed LSTM-based structure is modeled as follows. The input is modeled as $X = \{X_{t1}, X_{t2}, X_{t3}, \dots, X_{tn}\}$. The input is the time series function, which represents the vehicles at respective time t_i. $H = (h_1, h_2, \dots, h_n)$ represents the hidden states and $Y = \{Y_{t1}, Y_{t2}, Y_{t3}, \dots, Y_{tn}\}$ represents output of the cell. The computations are carried out as given in Eq. (4) and Eq. (5), respectively.

$$h_t = H(W_{hx}x_t + W_{hh}h_{t-1} + b_h) \tag{4}$$

$$p_t = W_{hy}y_{t-1} + b_y \tag{5}$$

Weight matrices and bias vectors are represented by W and b respectively.

Table 1
Hyper parameters.

Number of layers	4
Number of neurons in each layer	128
Optimizer	ADAM
Dropout	0.2
Activation function	Sigmoid
Epoch	600
Batch size	256
Training dataset	95%
Testing dataset	5%

The hyper parameters for the network are shown in Table 1. The objective function is modeled in Eq. (6) as a mean squared error (MSE) function. The MSE is reduced using an Adam optimizer based on the stochastic gradient descent process.

$$MSE = \sum_{t=1}^{n} (y_t - p_t)^2 \tag{6}$$

where, y_t represents the real value and p_t represents the predicted value.

3.2. RSU inside MEC

RSUs are installed inside the MEC unit. It assists in cooperative relay communication. Vehicles transmit the message packet according to the 802.11p protocol. As shown in Fig. 2 message packets consist of frames that are partitioned into safety messages, traffic information messages, and infotainment messages. A safety message consists of vehicular speed, latitude–longitude points, current time, and direction. Traffic information messages include information about routes, traffic congestion, number of vehicles in a particular region. This traffic information message field is processed at the RSU. In this way, RSU has all the information about vehicles in its proximity.

RSU provides assistance to promote cooperative communication. It helps to enhance bit error rate performance and increased throughput. The vehicles exchange messages via the 802.11 P/WAVE protocol. The signal-to-noise ratio (SNR) of the received message packet at the receiver is recorded and maintained in VIT and processed at MEC. The channel link quality against the corresponding transmission is also recorded at the edge server. At MEC the VIT is maintained and updated after every instant followed by the message transmission. If the received SNR between the primary transmitting and receiving vehicle is less than the threshold γ then the cooperative link will be activated to keep the QoS maintained. Amplify and forward (AF) relay technique is used for cooperative communication. MEC allocates the vehicles like the mobile relay nodes based on the measured link quality. The selection of the best relay candidate is chosen based on optimal stopping theory. To find the best optimal solution from the set of the pool, the agent before deciding to select the best relay, goes through the 1/e, i.e., 0.3678% of the candidate relays from a pool also called the Riemann approximation [25].

In literature, various techniques have been considered for relay selection using channel information from candidate relay nodes. However, the performance, of randomly relay selection degrades when the network size i.e., candidate relay nodes increases. Optimal stopping theory is modeled for relay selection for candidate vehicle relay nodes. This technique enhances the network performance and selects the best candidate relay node in less time.

The score for optimal relay selection is calculated based on the relative vehicle speed, direction, and received SNR. The optimal stopping theory is modeled as follows. Let vehicle $v_1 \in$ V is communicating with vehicle $v_3 \in$ V, then v_1 and v_3 are considered as the primary transmitter and primary receiver respectively. If the received packet SNR falls below the threshold γ, MEC selects a mobile relay node from V_s that contain all the vehicles $\in V$ other than v_1 and v_3 or selects RSU as a cooperative link based on channel conditions. Fig. 8 shows the cooperative relay communication. We assume that the proposed network is time-slotted and cooperative relay selection is performed at each time slot T.

We assume that only one secondary vehicle could act as a cooperative relay at a particular instant. To find a prospective cooperative relay vehicle, MEC observes the candidate relay nodes from V_s at each time slot. T be the time required for observing potential candidate relay. $C_V = \left\{RSU_1, RSU_2, RSU_3, \dots, RSU_n\right\} U \left\{V_{s1}, V_{s2}, V_{s3}, \dots, V_{sn}\right\}$ represents the candidate relay nodes. MEC based on VIT observes the candidate relay nodes from C_V sequentially. The reward is measured based on the channel link quality corresponding to each observation. The MEC stops at the kth observation, if the measured channel link quality $> \gamma$. Then MEC pass that information to V_p. V_p transmits the data packets to the selected node for a fraction of $(1 - \beta)$ of time $(T - K\tau)$, where $0 \le \beta \le 1$. The selected relay node amplifies the packet and then forwards the packet during residual time $\beta(1 - \alpha)(T - K\tau)$. To maximize the reward of selection MEC decides by comparing the instantaneous reward and expected reward. The instantaneous reward is determined based on the channel quality of the relay node being observed at that instant and the expected reward depends upon the future observation that could be obtained if keep looking for the following candidate relay nodes from C_V. We assume the channel as Rayleigh fading channel and model it as a finite-state markov Chain (FSMC). Eq. (7) shows the probability density function for the SNR received at the destination where r represents the average SNR.

$$f(\gamma) = \frac{1}{r} e^{\frac{\gamma}{r}} \tag{7}$$

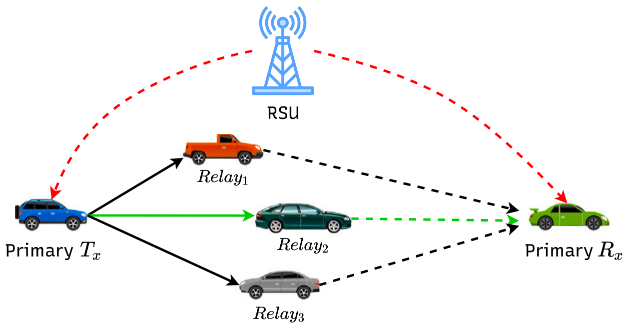

Fig. 8. Cooperative relay communication.

In FSMC, SNR is partitioned into i intervals and then grouped into finite state space. SNR thresholds are indicated in Eq. (8).

$$\gamma = \left\{\gamma_1 = 0, \gamma_2, \dots, \gamma_i, \gamma_{i+1} = \infty\right\} \tag{8}$$

Eq. (9) shows the probability of a secondary vehicle or RSU being in state I for the given channel.

$$q_i = \int_{\gamma i}^{\gamma i+1} f(\gamma)d\gamma = e^{\frac{\gamma_i}{r}} - e^{-\frac{\gamma_i+1}{r}}, i = 1, 2, \dots, I \tag{9}$$

Eq. (10) represents the transmission rate r_k between the primary vehicle and candidate Kth relay node.

$$r_k = W log(1 + \gamma_k) \tag{10}$$

The corresponding data rate $R = \left\{r_1, r_2, \dots, r_I\right\}$ is modeled as discrete random variable with same distribution as channel state is shown in Eq. (11).

$$P_r\left\{R = r_i\right\} = q_i \tag{11}$$

Let $X_k = R_k\Theta$ be defined as the transmission rate at kth observation, then the distribution of X_k is calculated from Eqs. (12) and (13).

$$P_0 = P_r\left\{X_k = x_0 = 0\right\} = (1 - \theta) \tag{12}$$

$$P_i = P_r\left\{X_k = x_0 = r_i\right\} = (q_u\theta) \tag{13}$$

where in Eqs. (11), (12), and (13), $1 \leq i \leq I, 1 \leq K \leq N$. Reward function is $Y_k = X_k c_k$ where $c_k = 1 - \frac{k\tau}{T}$. Y_k is the number of bits that could be transmitted in one slot. The MEC after receiving the reward Y_k at kth observation decides whether to stop or continue to observe the candidate relay node. Algorithm 2 shows the optimal stopping theory.

Algorithm 2: Relay Selection using Optimal Stopping

```
Step 1: Construct sequence set of candidate Vehicles: V_s = {V_s1, V_s2, V_s3, V_s4...V_sn}
Step 2: Start observation for Cooperative link
for (1 < k < N-1; k++)
Compute achievable transmission rate r_k and reward y_k. do
    S
end
tep 3: Compare the value of y_k and the expected reward. if y_k < expected reward then
    Proceed to observe the next candidate's secondary Vehicle ;
else
    Selects the current kth observation.
end
```

4. Experimentation

The experiment setup comprises three SDRs which include the national instrument (NI) N210 USRPs. The USRP is developed by the NI that provides a platform for the design and deployment of wireless communications systems. These USRP are connected to the laptops where LabVIEW software is used to control the USRP and for the baseband processing. LabVIEW is a graphical programming tool that provides a platform for the testing and validation of the research design and deployment of wireless communications

Fig. 9. Experiment setup.

Table 2
Tx and Rx Parameters.

Tx and Rx IQ sampling rate	500k
Tx frequency	5.9 GHz
Rx frequency	5.9 GHz
Tx and Rx gain	30 dB
Tx antenna	TX1
Rx antenna	RX 1
Modulation	QPSK
Filter at Tx end	Root raised cosine

systems. V2V transmitter and receiver software prototypes are implemented on LabView. Two USRPs connected with the laptops are placed in each car acting as OBU while the third USRP connected with the laptop act as RSU. The SBx daughterboard is installed in USRP having a frequency range between 2.2GHz–6 GHz with 100 MS/s ADC (analog to digital converter). V2V data transmitter and receiver virtual instruments (VI) are designed separately to establish a communication link between two systems i.e., between transmitter and receiver. The modulation technique which has been used during this experiment is quadrature phase-shift keying (QPSK) as it provides a better data rate along with less probability of bit error. The frequency which has been chosen for this purpose is 5.9 GHz. All the results calculated are taken on this frequency. Fig. 9 shows the experiment setup along with the highlighted path where the experiment has been performed. The USRP is connected to the laptop via ethernet cable. Furthermore, USRP is powered with standalone rechargeable batteries and the whole setup is placed on wheels i.e., inside a vehicle for experimentation.

4.1. Transmitter

Transmitter has been designed in LabVIEW 2015. Table 2 shows the parameters set at the transmitter end. The transmitting unit consists of USRP, a laptop, and a global positioning system (GPS) module. The GPS data collected is fetched using a GPS module at the transmitter end. This GPS data is modulated and transmitted via USRP by the transmitting vehicle. Fig. 10, shows the message that is being transmitted. Each transmitted packet consists of 128 message bits. The message contains the latitude and longitude of the vehicle's position and it also contains the information on time and date along with speed and direction.

4.2. Receiver

Like the transmitter, the receiver has also been designed in Lab-VIEW 2015. Table 2 shows the receiver parameters that have been set to receive the transmitted signal. USRP IP address has been set and then sampling rate and other parameters have been set to retrieve the transmitted signal. The received message is obtained at 5.9 GHz. After the received message is retrieved, the receiving vehicle will take an appropriate decision based on the received information. Fig. 11 shows received message.

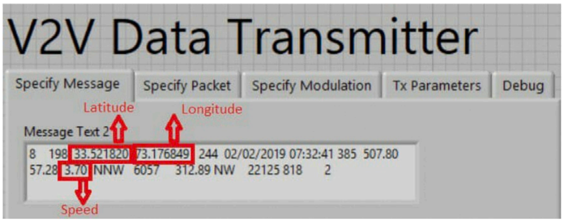

Fig. 10. Transmitted message.

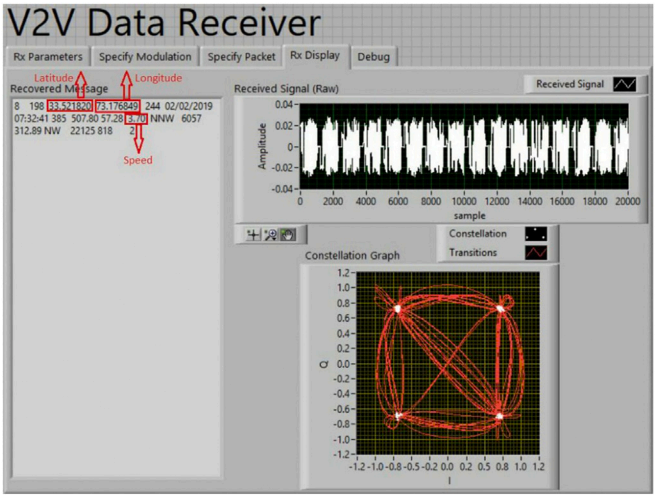

Fig. 11. V2V receiver GUI.

4.3. Measurements

RSU consists of USRP connected to the laptop via ethernet cable. Amplify and forward relay technique is implemented over the LabVIEW software running on the laptop. The signal received at the RSU is amplified and forwarded to the destination node. The capacity of the link is compared over the direct path and relay path using USRP as the RF frontend. The signal received at the destination vehicle is given by Eq. (14).

$$Y_{DL} = h_{DL}\sqrt{P_s}.x + n_{DL} \tag{14}$$

where, h_{DL} represents the channel response and P_s represents the power of the transmitted signal from the source vehicle, and n_{DL} represents the noise spectral density. Similarly, the signal received with the relay link is shown by Eq. (15). The signal is received at the destination node using a relay link and a direct link is added using maximal ratio combining (MRC) given by Eq. (16).

$$Y_{RL} = h_{RL}\sqrt{P_r}.x + n_{DL} \tag{15}$$

$$Y_{mrc} = Y_{RL} + Y_{DL} \tag{16}$$

Fig. 12 shows the capacity (bits/s) using relay link and direct link. Fig. 12 shows the comparison of the relay link and direct link between primary vehicles in terms of capacity (bits/s). The experiment is performed multiple times at different varying transmit gains between (5, 35). In direct link primary vehicles i.e., source vehicle and destination vehicle communicate directly without the involvement of RSU. In cooperative communication/relay-based communication primary vehicles communicate with the assistance of RSU or secondary candidate relay nodes. Fig. 12 shows the significant performance improvement obtained in cooperative communication as compared to direct link.

Fig. 9, shows the highlighted path where the on-road experiment is performed. All experiments are conducted on this path. The overall path at which the testing is done is 1000 m. After performing several experiments, the results have been calculated. As the vehicle moves away from the transmitter the SNR decreases and also we have studied the effect of mobility on SNR. Fig. 13 shows the trend of degradation of SNR with respect to the speed of the vehicle.

From Fig. 13, it is shown that cooperative communication/relay based communication performs better than direct communication. However, utilizing relays leads to an increase in the cost of infrastructure, by placing RSU after every instant. We proposed the

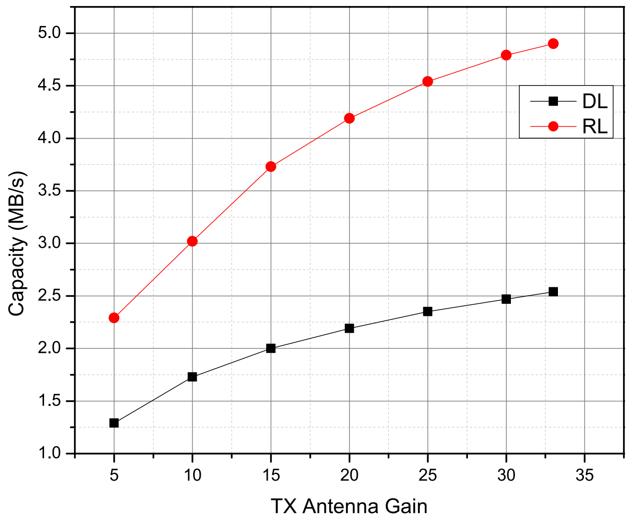

Fig. 12. Direct and relay based communication.

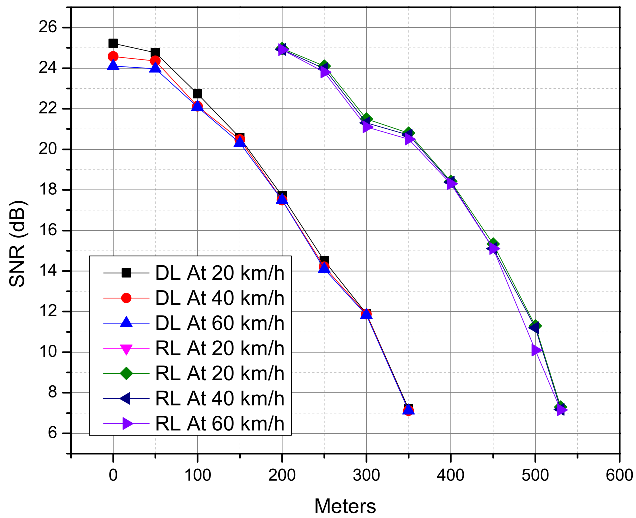

Fig. 13. Direct and relay based communication at different velocity.

NFV-enabled RSU inside MEC. At MEC, the LSTM-based machine learning algorithm predicts road traffic. Based on road traffic RSU enhance its transmitting range when required. In the following section by performing a simulation we evaluated the performance of the proposed scheme.

5. Simulation

Simulations are performed in network simulator ns-3. SUMO is integrated with ns-3 to generate vehicular traffic in an urban area. Vehicular traffic is randomly generated and observed for 12 h. The traffic flow is observed at particular instants and recorded with respect to the time. The dataset is maintained based on the traffic information recorded. The neural network is built and trained over the generated dataset. The LSTM-based deep learning model is built and applied to predict road traffic. The learning curves for the trained model are shown in Fig. 14. Fig. 14 shows the validation loss and training loss. The validation loss is computed the same way as the training loss using a loss function as defined in Eq. (6). Fig. 14 shows the validation loss nearly equal to training loss which means that model is neither overfitted nor under fitted.

The trained model is applied for predicting the traffic flow. The observed and the predicted curve are shown in Fig. 15. The model accuracy is evaluated from parameters such as; mean absolute percentage error (MAPE), mean absolute error (MAE) and root mean square error (RMSE). The MAPE, MAE, and RMSE are defined in Eqs. (17), (18) and (19), where y_i represents the observed

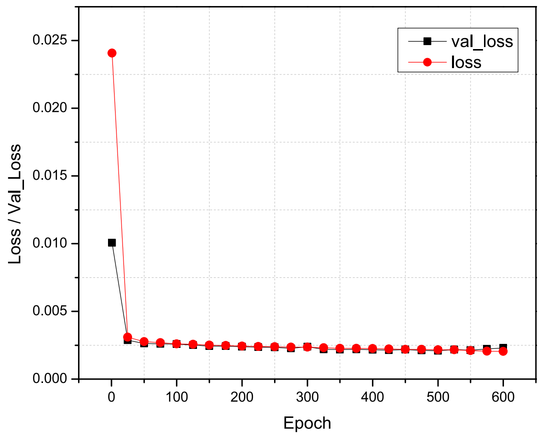

Fig. 14. Learning curve.

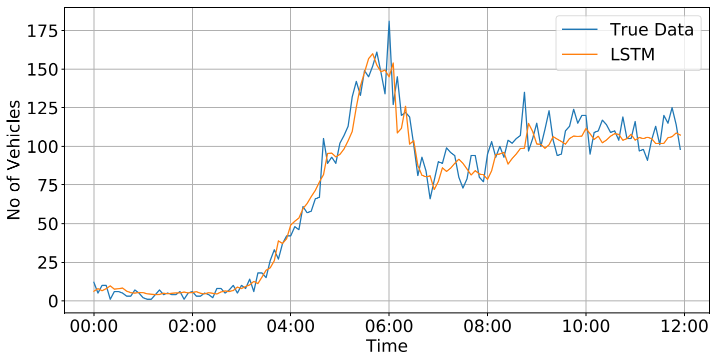

Fig. 15. Predicted and observed traffic flow.

Table 3
Evaluation metrics.

MAPE	18.6676%
MAE	7.158%
RMSE	9.864%

vehicles at time instant i and y_i^p represents the predicted vehicles for that time.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_i^p}{y_i}\right| \tag{17}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_i^p\right| \tag{18}$$

$$RMSE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_i^{p2}\right|^{\frac{1}{2}} \tag{19}$$

Table 3 shows the evaluated parameters. Fig. 16 shows the packet delivery ratio (PDR) with respect to the transmit power. The 100 vehicles are considered in the area of 1500 × 750 m^2 generated using SUMO. The 100 vehicles are considered so that they can move freely. Ad-hoc on-demand distance vector (AODV) routing protocol is used. The distance between most of the vehicles is kept at more than 300 meters so that vehicles can communicate via vehicle to RSU (V2R) and RSU to Vehicle (R2V). The RSU are placed at specific coordinates at (200, 150), (700, 250), and (1200, 500). The RSU coverage range is directly proportional to its transmission power. Fig. 16 shows the impact of transmit gain on PDR. At less than 20dBm transmit gain, the PDR observed is less than 80%. The PDR increases to more than 90% with the increase in transmission power.

To evaluate the performance of optimal relay selection, we compared the scheme with the random relay selection technique. Fig. 17 shows the performance comparison of optimal relay selection and random relay selection. The performance is measured by increasing the number of secondary candidate vehicles that can assist in cooperative communication. In the random relay selection

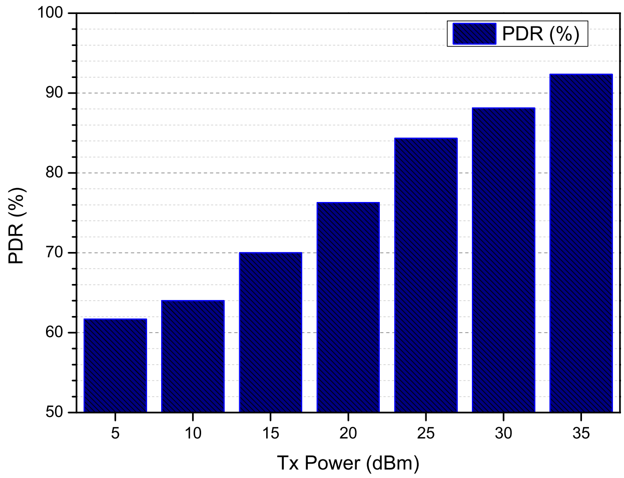

Fig. 16. PDR concerning transmit power.

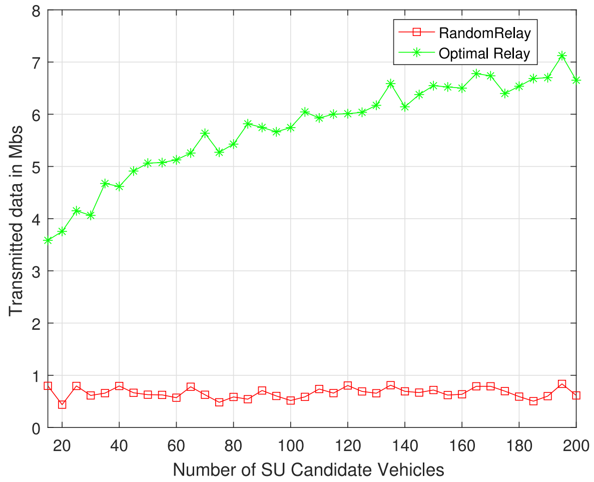

Fig. 17. Transmitted data using random relay and optimal relay.

procedure, the primary vehicle pair selects the secondary candidate vehicle without measuring channel conditions and signal strength. Fig. 17 shows that the performance substantially improved with the selection of relays for transmitting data compared to random relay selection.

The impact of cooperative communication and without cooperative communication on PDR is shown in Fig. 18. In cooperative communication, the secondary candidate vehicle is selected utilizing the optimal relay selection technique. The number of vehicles increased from 25 to about 200. Fig. 18 shows that when the number of vehicles is less than 50, the performance is almost similar in both cases. When the number of vehicles increased to 100, the PDR in the case of cooperative communication is nearly equal to 90%, and without cooperation, it is less than 85%. In dense vehicular traffic, the PDR falls below 65% when the number of vehicles exceeded more than 150 in the case of without cooperative communication. However, PDR does not fall below 75% in the case of cooperative communication.

6. Conclusion

The on-road evaluation has shown that the signal strength deteriorates with the increase in distance between the transmitter and the receiver or due to bad channel conditions. However, by using the relay link the quality-of-service (QoS) in a vehicular environment could be improved. Moreover, we evaluated the network function virtualization (NFV) enabled roadside units (RSU) inside the mobile edge computing (MEC). Since RSU are only placed in dense traffic regions and due to their fixed positions, they cannot adapt to real-time traffic to provide wide network coverage. In this work, we exploited the NFV property to vary the transmit power of RSU to enhance the coverage range. Long short-term memory (LSTM) based machine learning model is applied at the MEC to predict the traffic flow based on the vehicle information table (VIT) maintained. Based on predicted traffic flow, MEC assists RSU

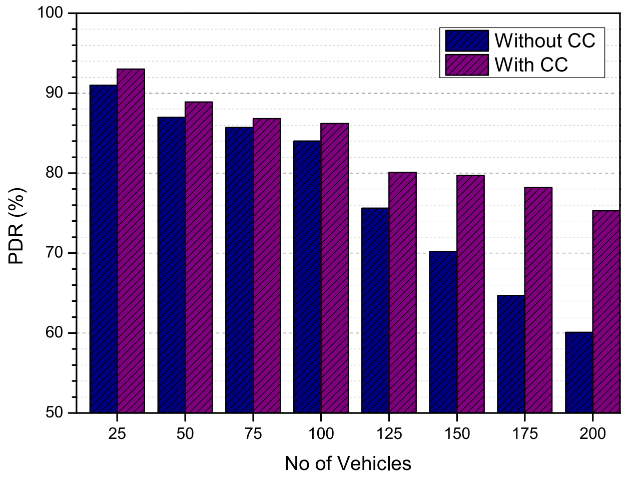

Fig. 18. Performance evaluation in cooperative communication and without cooperative communication.

based on the prediction to increase the transmit power when required. MEC also provides support to the vehicles in cooperative communication, for the selection of relay. The optimal stopping approach is applied to select the best candidate relay in a short time. The result shows that the optimal stopping approach outperforms, with the increase in the number of vehicles compared to the random relay selection.

7. Future work

In future, we will exploit UAV as portable RSU. Due to UAV agility, they could assist on-road vehicles even in white coverage regions. The cost of infrastructure would be further reduced by using UAV instead of fixed RSU for providing services to the vehicles. Since UAV, would be deployed in 3D space, we will explore the optimal placement of UAV to assist vehicles. Further, we will also exploit the NFV and edge computing capabilities at UAV considering the battery constraints.

Declaration of competing interest

No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.compeleceng.2022.108348.

Data availability

No data was used for the research described in the article.

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References

[1] Durga R, Poovammal E, Ramana Kadiyala, Jhaveri Rutvij H, Singh Saurabh, Yoon Byungun. CES blocks—A novel chaotic encryption schemes-based blockchain system for an IoT environment. IEEE Access 2022;10:11354–71. http://dx.doi.org/10.1109/ACCESS.2022.3144681.

[2] Barmpounakis Sokratis, George Tsiatsios, Michael Papadakis, Evangelos Mitsianis, Nikolaos Koursioumpas, Nancy Alonistioti. Collision avoidance in 5G using MEC and NFV: The vulnerable road user safety use case. Comput Netw 2020.

[3] Singhal Vivek, Jain SS, Anand Divya, Singh Aman, Verma Sahil, Kavita, et al. Artificial intelligence enabled road vehicle-train collision risk assessment framework for unmanned railway level crossings. IEEE Access 2020;8:113790–806. http://dx.doi.org/10.1109/ACCESS.2020.3002416.

[4] Barakabitze Alcardo Alex, Ahmad Arslan, Mijumbi Rashid, Hines Andrew. 5G network slicing using SDN and NFV: A survey of taxonomy, architectures and future challenges. Comput Netw 2020;167:106984.

[5] Abdelwahab Sherif, Bechir Hamdaoui, Mohsen Guizani, Taieb Znati. Network function virtualization in 5G. IEEE Commun Mag 2016.

[6] Singh Pranav Kumar, Nandi Sunit Kumar, Nandi Sukumar. A tutorial survey on vehicular communication state of the art, and future research directions. Veh Commun 2019;18:100164.

[7] Xu Lingwei, Zhou Xinpeng, Li Xingwang, Jhaveri Rutvij H, Gadekallu Thippa Reddy, Ding Yuan. Mobile collaborative secrecy performance prediction for artificial IoT networks. IEEE Trans Ind Inf 2022;18(8):5403–11. http://dx.doi.org/10.1109/TII.2021.3128506.

[8] Zhang Yuexia, Zhao Yifei, Zhou Ying. User-centered cooperative-communication strategy for 5G internet of vehicles. IEEE Internet Things J 2022;9(15):13486–97. http://dx.doi.org/10.1109/JIOT.2022.3143124.

[9] Wang Shujuan, Zhang Qian, Chen Guangchao. V2V-CoVad: A vehicle-to-vehicle cooperative video alert dissemination mechanism for internet of vehicles in a highway environment. Veh Commun 2022;33:100418.

[10] Wang Xiaojie, Ning Zhaolong, Hu Xiping, Ngai Edith C-H, Wang Lei, Hu Bin, et al. A city-wide real-time traffic management system: Enabling crowdsensing in social internet of vehicles. IEEE Commun Mag 2018;56(9):19–25.

[11] Ni Yuanzhi, He Jianping, Cai Lin, Bo Yuming. Data uploading in hybrid V2V/V2I vehicular networks: Modeling and cooperative strategy. IEEE Trans Veh Technol 2018;67(5):4602–14.

[12] Liu Jianqi, Wan Jiafu, Zeng Bi, Wang Qinruo, Song Houbing, Qiu Meikang. A scalable and quick-response software defined vehicular network assisted by mobile edge computing. IEEE Commun Mag 2017;55(7):94–100.

[13] Feng Jingyun, Liu Zhi, Wu Celimuge, Ji Yusheng. Mobile edge computing for the Internet of vehicles: Offloading framework and job scheduling. IEEE Veh Technol Mag 2018;14(1):28–36.

[14] Chen Chen, Chen Lanlan, Liu Lei, He Shunfan, Yuan Xiaoming, Lan Dapeng, et al. Delay-optimized V2V-based computation offloading in urban vehicular edge computing and networks. IEEE Access 2020;8:18863–73.

[15] Wu Yuying, Zheng Jun. Modeling and analysis of the local delay in an MEC-based VANET for a suburban area. IEEE Internet Things J 2022;9(9):7065–79. http://dx.doi.org/10.1109/JIOT.2021.3116195.

[16] Barmpounakis Sokratis, Tsiatsios George, Papadakis Michael, Mitsianis Evangelos, Koursioumpas Nikolaos, Alonistioti Nancy. Collision avoidance in 5G using MEC and NFV: The vulnerable road user safety use case. Comput. Networks 2020;172:107150.

[17] Siddiqi Murtaza Ahmed, Iwendi Celestine, Jaroslava Kniezova, Anumbe Noble. Analysis on security-related concerns of unmanned aerial vehicle: attacks, limitations, and recommendations. Math Biosci Eng 2022;19(3):2641–70.

[18] Saad Malik Muhammad, Bhatti Farrukh Aziz, Zafar Adnan, Jangsher Sobia, Kim Dongkyun, Maqsood Moazam. Air-interface virtualization using filter bank multicarrier and orthogonal frequency division multiplexing configurations. Trans Emerg Telecommun Technol 2021;32(2):e4154.

[19] Khan Tayyaba S, Khattak HA, Almogren A, Shah MA, Ud Din I, Alkhalifa I, Guizani M. 5G vehicular network resource management for improving radio access through machine learning. IEEE Access 2020;8:6792–800.

[20] Ahmad Syed Amaar, Hajisami Abolfazl, Krishnan Hariharan, Ahmed-Zaid Farid, Moradi-Pari Ehsan. V2V system congestion control validation and performance. IEEE Trans Veh Technol 2019;68(3):2102–10.

[21] Ng Hai Heng, Vasudha Ramnath, Hoang Anh Tuan, Kwan Charlene, Zhou Baitao, Cheong Joanne, et al. BESAFE: Design and implementation of a DSRC-based test-bed for connected autonomous vehicles. In: 2018 21st international conference on intelligent transportation systems. IEEE; 2018, p. 3742–8.

[22] Wang Tong, Hussain Azhar, Cao Yue, Gulomjon Sangirov. An improved channel estimation technique for IEEE 802.11 p standard in vehicular communications. Sensors 2019;19(1):98.

[23] H Khan Zawar, Imran Waheed, Azeem Sajid, S Khattak Khurram, Gulliver T Aaron, Aslam Muhammad Sagheer. A macroscopic traffic model based on driver reaction and traffic stimuli. Appl Sci 2019;9(14):2848.

[24] Lighthill Michael James, Whitham Gerald Beresford. On kinematic waves II. A theory of traffic flow on long crowded roads. Proc R Soc A 1955;229(1178):317–45.

[25] Borrego Carlos, Borrell Joan, Robles Sergi. Efficient broadcast in opportunistic networks using optimal stopping theory. Ad Hoc Netw 2019;88:5–17.

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