Department of Computer Science and Information Engineering
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Dissertation presentation

Intelligent Transmission Control Schemes for Enhancing Reliability in Vehicular Networks

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Outline

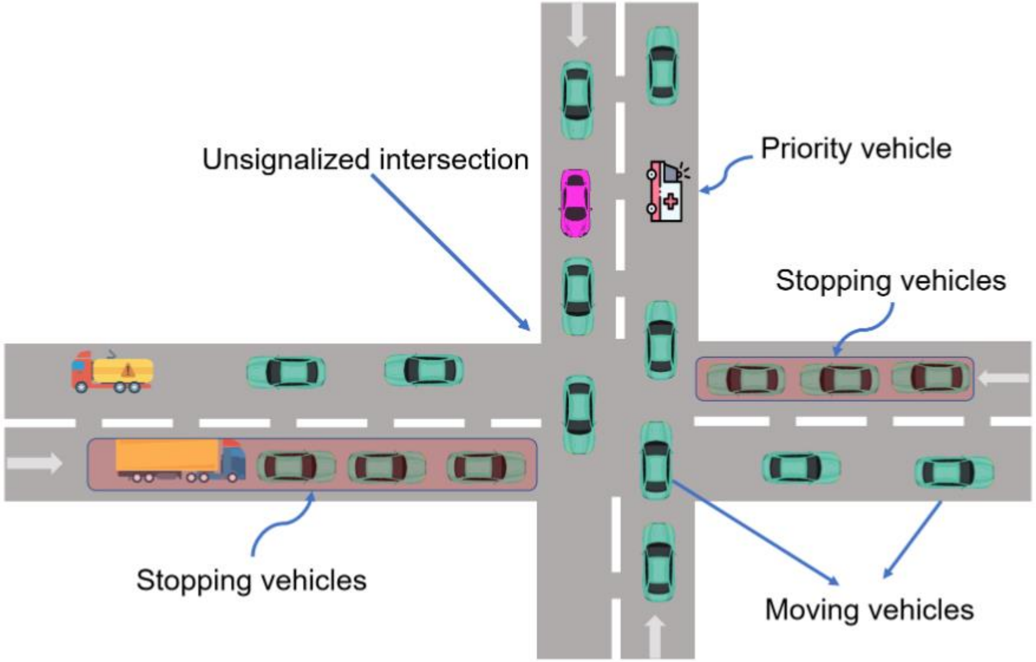
- Motivation & literature review
- Problem identification
- Our proposed methods
- Evaluation results
- Conclusion

Motivation

- Factors influence the reliability of vehicular communications
  - × Channel congestion ⟵ Our main focus
  - × Security attacks

- Mitigating vehicular network congestion can be done by
  - ✓ Increasing V2V channel bandwidth
  - ✓ Utilizing resource allocation ⟵ 3GPP specification
  - ✓ Controlling sending data rate ⟵ Under development

Source: our work [2]



Channel congestion in V2V communications

Literature Review (1/2)

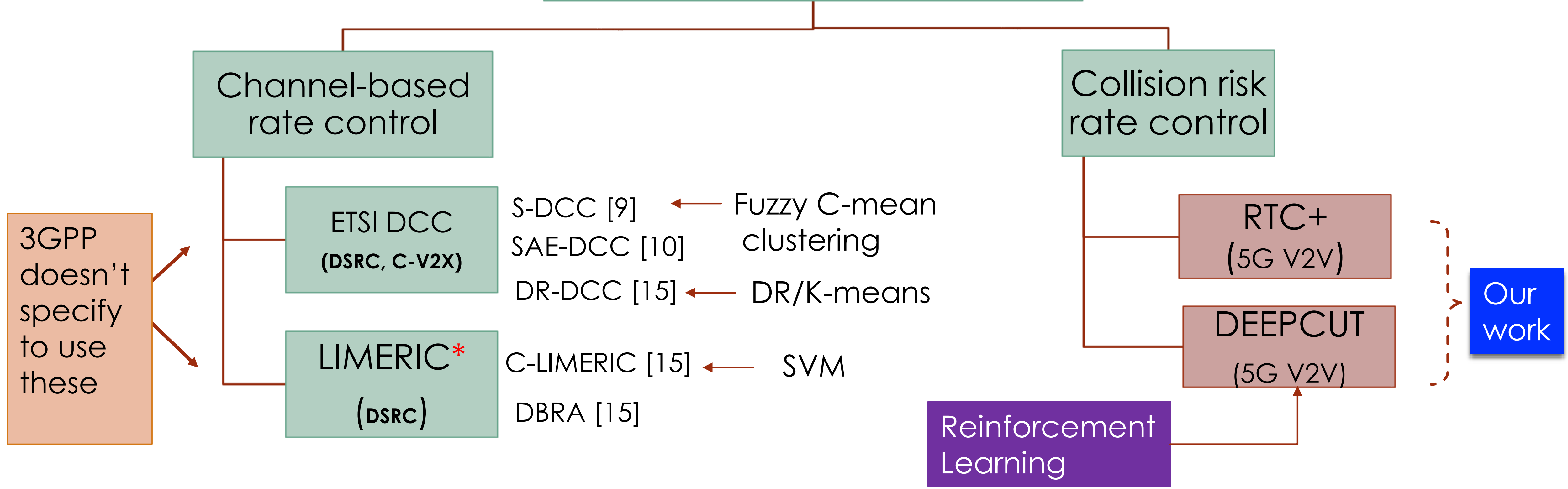
Study	Support 5G V2X	Safety/risk factor	Fairness factor	Machine learning support	Measurement metric	Learning model
DCC [1] [12]	✓	✗	✗	✗	PDR, CBR	Linear data rate adjustment
S-DCC [9]	✓	✗	✗	✓	CBR	Fuzzy C-Mean clustering
SAE-DCC [10]	✗	✗	✓	✗	CBR	Age-of-Information Optimization
DR-DCC [15]	✓	✗	✗	✓	CBR	Deep Q-learning, K-Means
LIMERIC [14]	✗	✗	✓	✗	CBR, IPG	Adaptive data rate control
Ours	✓	✓	✓	✓	PDR, CBR, CR	Distance-risk optimization, Double Deep Q-learning

Literature Review (2/2)

*

$$R_j(t) = (1-\alpha) * R_j(t-1) + \beta * (CBR_T - CBR(t-1)) \quad (1)$$

$CBR(t-1)$ and CBR_T are the measured CBR at time $t-1$ and the target channel load, respectively. α and β are convergence factors influencing the convergence and stability of states.



Our Contributions

- Two novel intelligent risk-based rate control methods to suggest the proper data rate of broadcasting V2V messages.

- The vehicles can automatically adjust their sending rate based on the risk assessment. Therefore, the system can reduce the redundant sending data to mitigate the channel congestion while still maintaining the safety.

- The evaluation results demonstrate the significant effects of the method in reducing the potential congestion for V2X applications, particularly maintaining safety (cut up 16% redundant data while increasing 22% packet delivery rate compared with baseline models)

Problem Statement

- Input: A wireless channel with limited bandwidth DR_{max}, N vehicles broadcasting messages
- Output: A maximum number of receiver vehicles can receive data at a specific quality-of-service
- Goal:
  - ✓ Channel congestion mitigation
  - ✓ Data transmission control without impacting safety
- Challenges
  1. There must have an efficient mechanism to determine which vehicles are the ones to cut down their sending rate
  2. The safety requirement must be the priority, i.e., the vulnerable-to-collision vehicles should be prioritized to use the channel.

  Trade-off: determining a proper broadcasting rate for utilizing channel usage and guaranteeing driving safety

Rate Control vs Resource Allocation

- **Rate control**
  - Manage the congestion through adjusting the sending rate of connected vehicles

Reduce

Data rate (R)= $\frac{Number\ of\ messages}{Time\ interval}$

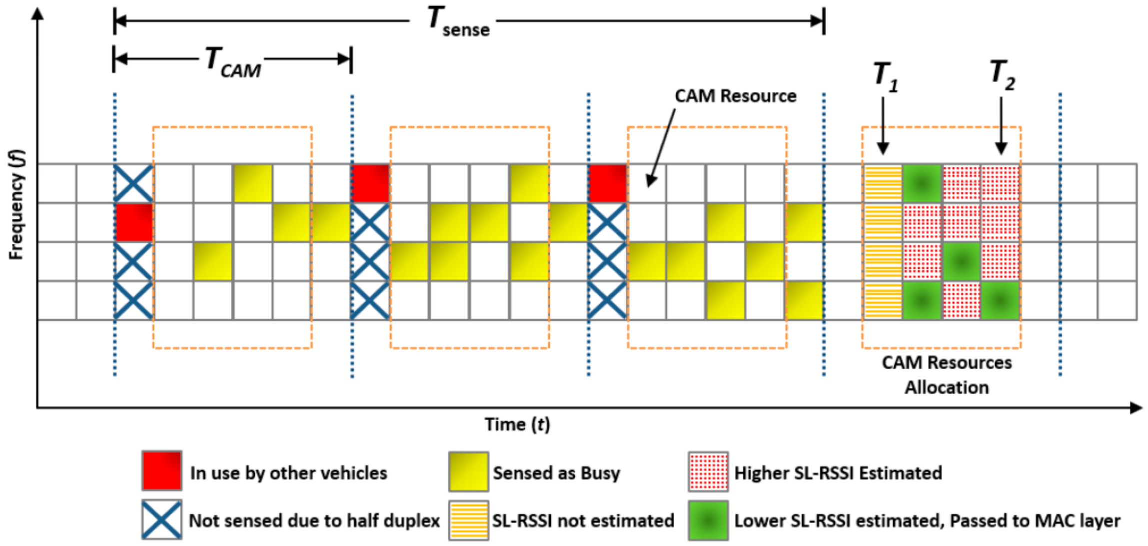
increase

LIMERIC

$$R_j(t) = (1-\alpha) * R_j(t-1) + \beta * (CBR_T - CBR(t-1)) \quad (1)$$

$CBR(t-1)$ and CBR_T are the measured CBR at time $t-1$ and the target channel load, respectively. α and β are convergence factors influencing the convergence and stability of states.

- **Resource allocation**
  - Sensing-based semi-persistent scheduling (SB-SPS) manages the congestion through scheduling resource reservation interval (RRI) and power transmission for connected vehicles (T_{CAM})



System Model (1/2)

- 5G V2V with a fixed bandwidth DR_{max}
- N connected vehicles
- At the time $t,$ vehicle i is sending data at a rate DR_i^t

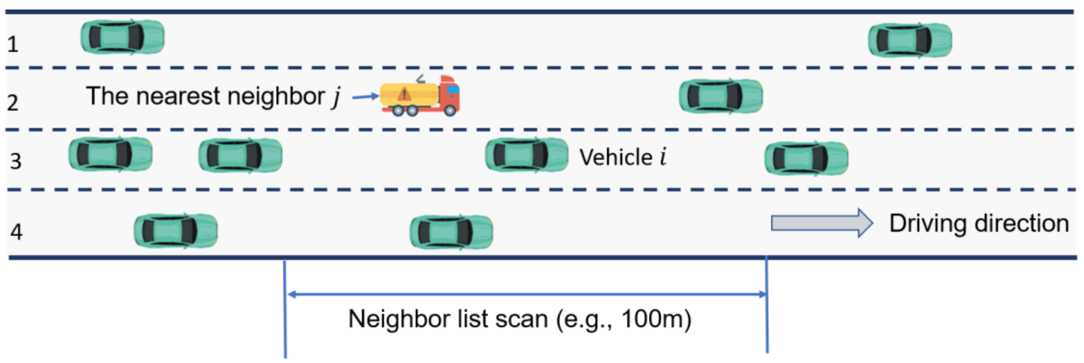
$DR_i^t = \frac{S_i^t}{T_i^t}$, where S_i^t is the number of messages vehicle i sent within a time interval T_i^t, e.g., 100ms.

- The sum rate with N vehicles at the time t

$DR_{sum} = \sum_{i=1}^{N} DR_i^t$ (1)

- The channel congestion occurs if DR_{sum} >= DR_{max}

- We don't consider the impact of wireless path loss/interference in this work (using the simulator's *default resource allocation mechanism*)



System Model (2/2)

- Packet delivery rate (PDR) is defined as the ratio of successfully received messages to the total number of messages sent by vehicle i

$$PDR_i^t = \frac{\frac{1}{N_i^t}\sum_{j=1}^{N_i^t} \lambda_{i,j}^t}{\mu_i^t} \quad (2)$$

where

+ μ_i^t is the number of transmitted messages by vehicle i to the vehicles

+ $\lambda_{i,j}^t$ denotes the number of messages successfully received by N_i^t vehicles

within a time interval T_i^t

Problem Formulation

The problem of network congestion mitigation is equal to the objective of the following optimization problem function:

$$\underset{DR_i^t}{\operatorname{argmax}} \sum_t^T \sum_1^N PDR_i^t \qquad (3)$$

subject to

$1. DR_i^t \geq DR_{min},\ i \in [1, N], \forall\ t \in [0,1,..,T]$ Minimum data rate for V2X applications

$2. DR_{sum}^t \leq DR_{max},\ \forall\ t \in [0,1,..,T]$ Channel capacity

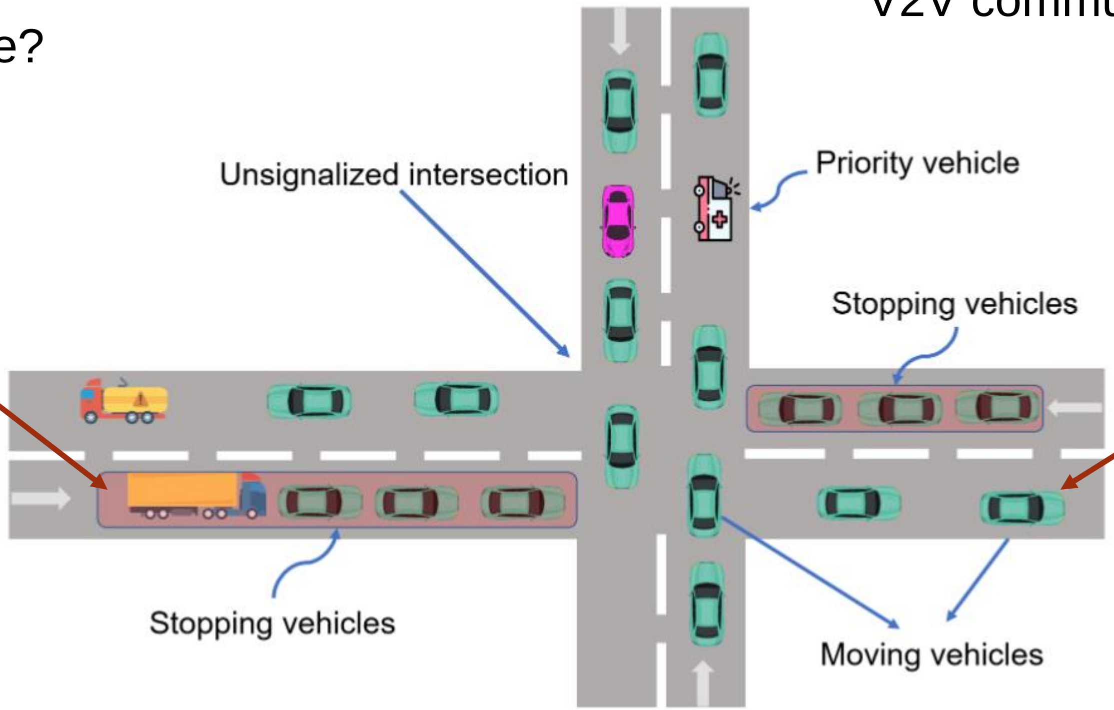
The Key Question

Which vehicles (low-risk or high-risk) should we reduce the sending/broadcasting rate?

How to determine?

V2V communications under congestion

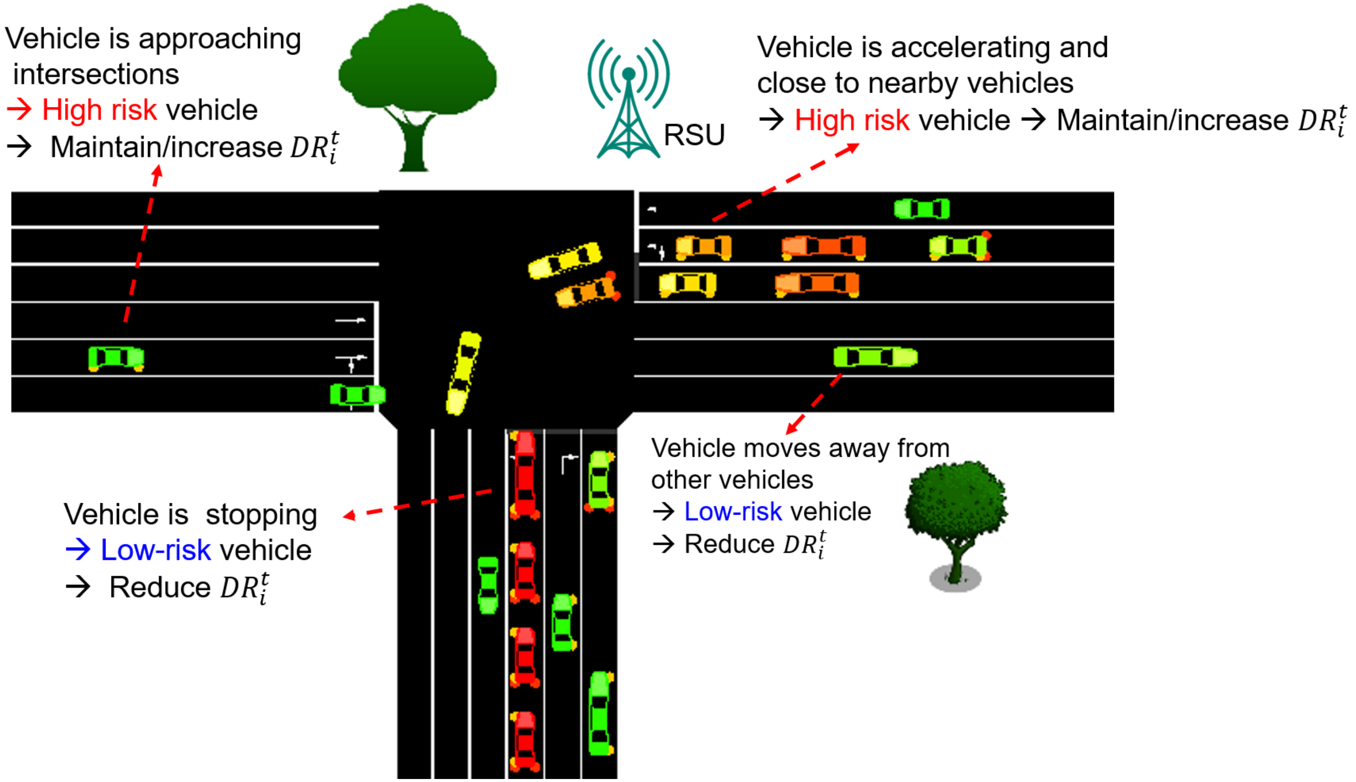
Low-risk vehicles



High-risk vehicles

Our Idea to Reduce Vehicles' Sending Rate

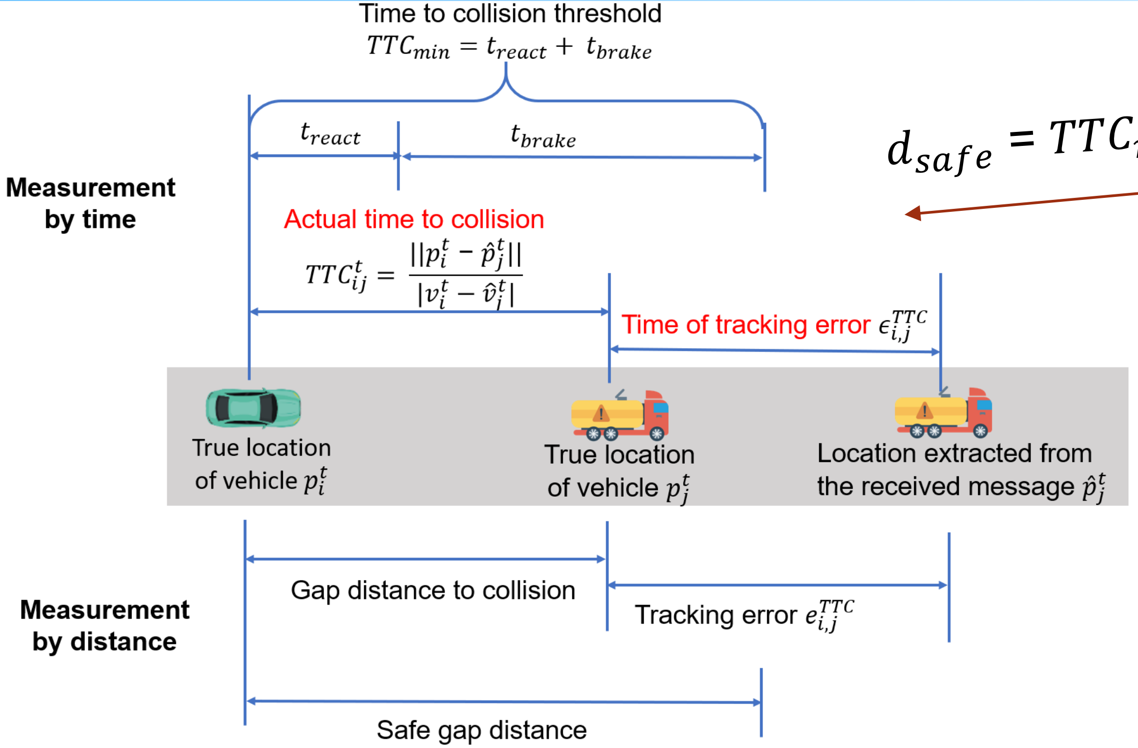
- **Decrease** the data rate of low-risk vehicles
- **Maintain** the data rate of high-risk vehicles (if that is the current state)
- **Increase** the data rate of high-risk vehicles (if the state is a transition from low risk to high risk)



Our idea is to gain two goals:

1. Help to mitigate congestion
2. Maintain the safety

How to Define Collision Risk?



d_{safe} = TTC_{min} $*v_i$

Example: v_i^t = 72km/h (20m/s); TTC_{min}= 2

d_{safe} = $v_i^t * TTC_{min}$ = 40m

- $RIS_{i,j}^t$: the collision risk of two vehicles i and j at the time t

$$RIS_{i,j}^t = \begin{cases} 1 \;\; if \;\; d_{i,j}^t - \alpha \leq d_{safe} \\ 0 \qquad\qquad\qquad otherwise \end{cases} \quad (4)$$

α is an expected error of distance estimation
d_{safe} is the threshold for a safe distance
$d_{i,j}^t$ is the distance between the vehicle i and the vehicle j

- $d_{i,j}^t$ can be estimated through
  1. Extracting from received messages
  2. Self-tracking through cameras/signal-based localization
- High risk vehicle: $RIS_{i,j}^t$ = 1
- Low risk vehicle: $RIS_{i,j}^t$ = 0

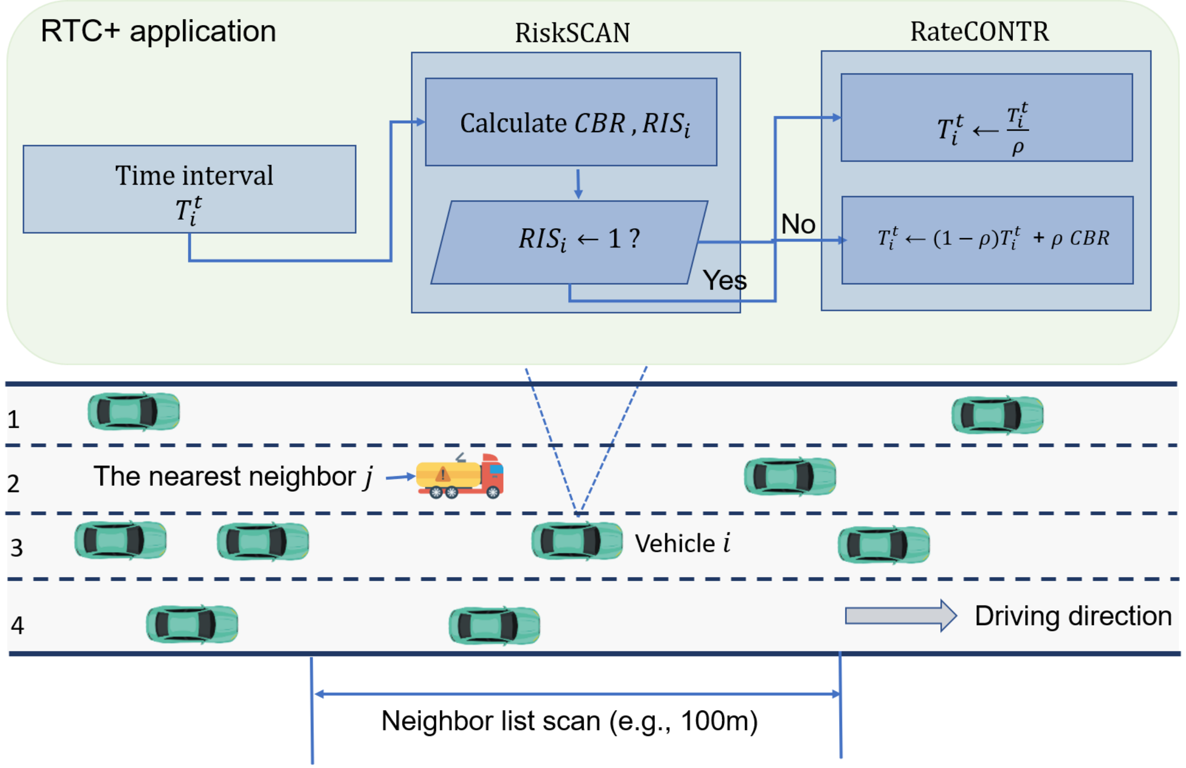
RTC+: Simple Risk-Based Transmission Control

- Sending rate $DR_i^t = \frac{s_i^t}{T_i^t}$

T_i^t is the time interval

- Reducing the sending rate by increasing the time interval T_i^t

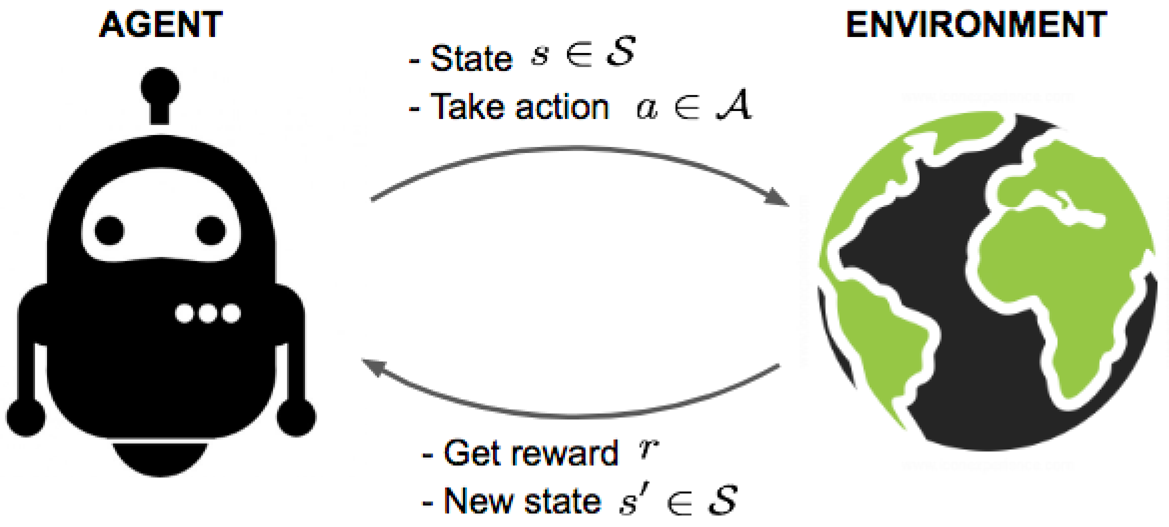
- The parameter ρ is an adjustable variable, $\rho = 0.9$ in default



Source: our work [1]

DEEPCUT: Smart DRL-based Transmission Control

- We use Deep Reinforcement Learning
  - ✓ Smart: Vehicles can interact with V2V communications to adjust learning strategy and broadcasting rate properly
  - ✓ Efficiency: Does not require labeled datasets for training
- We use the Double Deep Q-Networks (DDQN) type
  - ✓ Easy to implement
  - ✓ Action space is discrete so estimating max. Q-value is feasible.



Source: Lil'Log

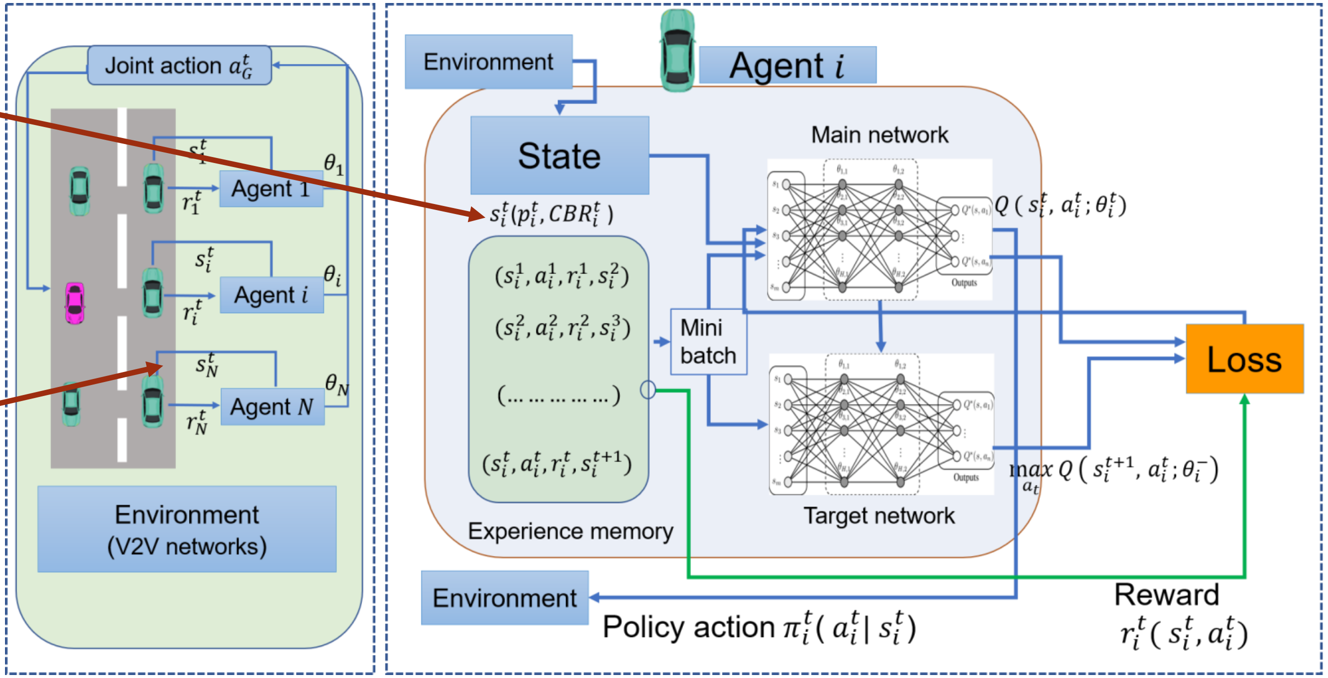
Deep Reinforcement Learning Definition (1/3)

- State: Each vehicle state s_i^t at the time t represents by
  1. Position p_i^{t-1}
  2. Data rate DR_i^t
  3. Channel busy ratio CBR^{t-1}

  For multi-agent environment

  $s^t = \{s_1^t, s_2^t, \ldots., s_N^t\}$
- Action: Each vehicle takes an action a_i^t to adjust DR_i^t
  1. $a_i^t = \{-\beta, 0, \beta\}$

β is the step change for the sending rate DR_i^t



Our DDQN-based model architecture

Deep Reinforcement Learning Definition (2/3)

The problem of network congestion mitigation is equal to the objective of the following optimization problem function:

$$\underset{a_i^t}{\operatorname{argmax}} \sum_{k=0}^{\infty} \gamma^k \, r_i^{t+k} \qquad (5)$$

subject to

1. $DR_i^t \geq DR_{min},\ i \in [1, N], \forall\, t \in [0,1,..,T]$
2. $DR_{sum}^t \leq DR_{max},\ \forall\, t \in [0,1,..,T]$

where r_i^t is the reward for the action a_i^t
γ^k is the discount factor

The goal of the DRL-based optimization problem is to optimize the policy $\pi\ (a_i^t | s_i^t)$ to maximize the cumulative reward values, i.e., total number of all transmitter vehicles' neighbors that can decode the messages at time t.

Deep Reinforcement Learning Definition (3/3)

- Reward

$$r_i^t = \begin{cases} a \text{ if } CBR^t > C_{threshold} \,\&\, RIS_{i,j}^t = 1 \\ b \text{ if } CBR^t > C_{threshold} \,\&\, RIS_{i,j}^t = 0 \\ c \text{ if } CBR^t < C_{threshold} \,\&\, RIS_{i,j}^t = 1 \\ d \text{ if } CBR^t < C_{threshold} \,\&\, RIS_{i,j}^t = 0 \end{cases} \quad (6)$$

$C_{threshold}$ is the CBR threshold to determine the channel busy, e.g., = 0.85 (85%).

- The value of a, b, c, d are adjustable values but should be proportional to the state of the channel and risks

- The higher risk + congestion the action causes, the higher penalty it gets (negative value)

- For example, a=-10, b=-2, c=-4, d = 2

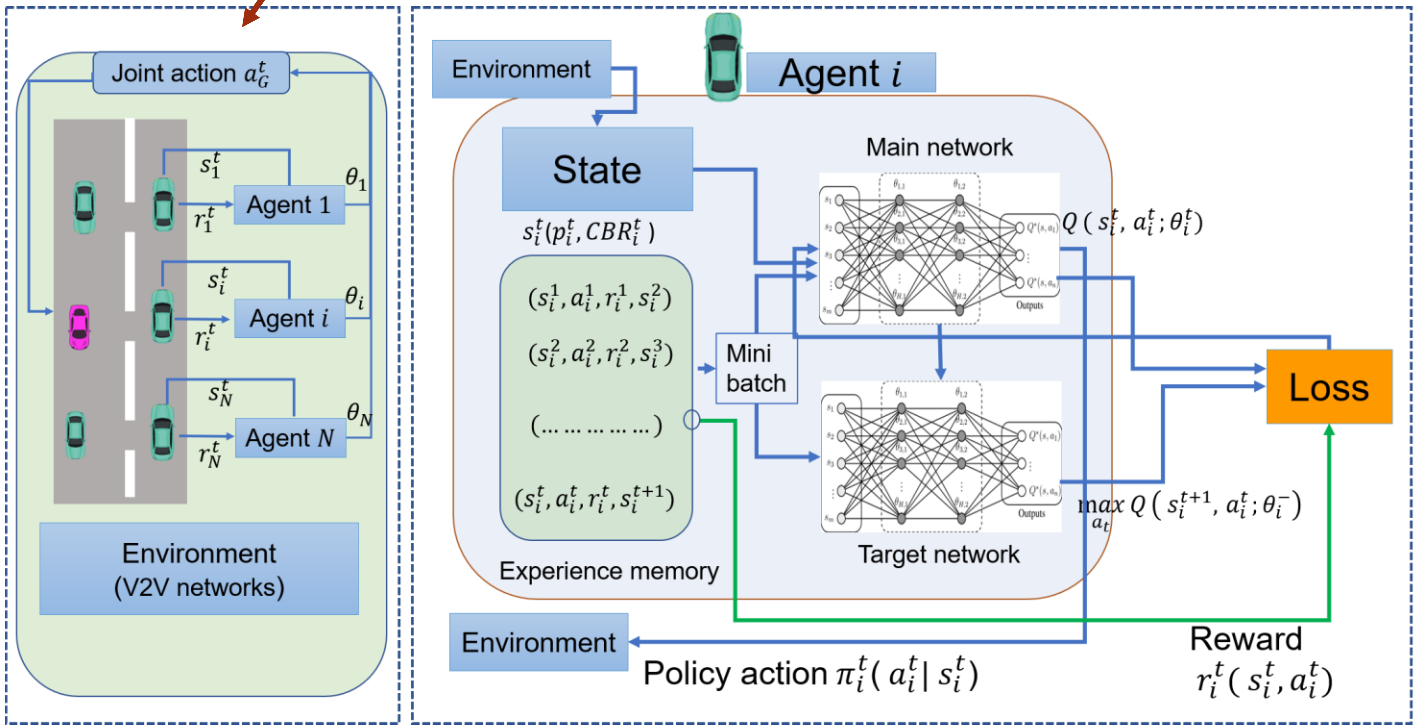
DDQN-based Transmission Control Algorithm

Multi-agent model to make a consensus decision

Algorithm 2: DDQN-based transmission control algorithm for vehicles

Data: $RIS_i^t, \eta, DR_i^t, k, DR_{min}, N, \beta$
Result: DR_i^t

Function TransControl($RIS_i^t, \eta, DR_i^t, k, DR_{min}, N, \beta$)
  Initialize replay memory Ω capacity $|N|$; mini-batch k; learning rate η,
  Initialize action value step β, Q-function with random weights θ
  Initialize Target-$\hat{Q}$-function with the same weights $\theta^{-1} \leftarrow \theta$
  for $i = 1$ *to* N **do**
    Observe the state $s_i^0(p_i^0, CBR^0)$ and action a_i^0 (DR_{min}) with policy $\pi(a_i^0|s_i^0)$;
  end
  for *episode* $= 1$ *to* M **do**
    for $i = 1$ *to* N **do**
      for *time step* $t = 1$ *to* T **do**
        Observe $s_i^t, a_i^t, r_i^t, \gamma^t$;
        Store transition $(s_i^{t-1}, a_i^t, r_i^t, \gamma^t, s_i^t)$ in replay memory Ω;
        Select $a_i^t \leftarrow \arg\max_{a_i^t \in (A)} Q^*(s_i^t, a_i^t; \theta_i)$ in the target-$\hat{Q}$-network;
        Send messages at the rate DR_i^t at the guide of a_i^t and observe reward r_i^t;
        Calculate s_i^{t+1};
        Store the experience $(s_i^t, a_i^t, r_i^t, \gamma^t, s_i^{t+1})$;
        Estimate the loss,
        $Loss(\theta_i) \leftarrow \mathbb{E}_\pi[y_i^{DDQN} - Q(s_i^t, a_i^t; \theta_i))^2]$;
        Update $\theta_i \leftarrow \theta_i - \eta \nabla_{\theta_i} Loss(\theta_i)$;
        Update the target $\hat{Q}$-network with $\theta_i^{-1} \leftarrow \theta_i$;
      end
    end
end



DDQN-based transmission control architecture

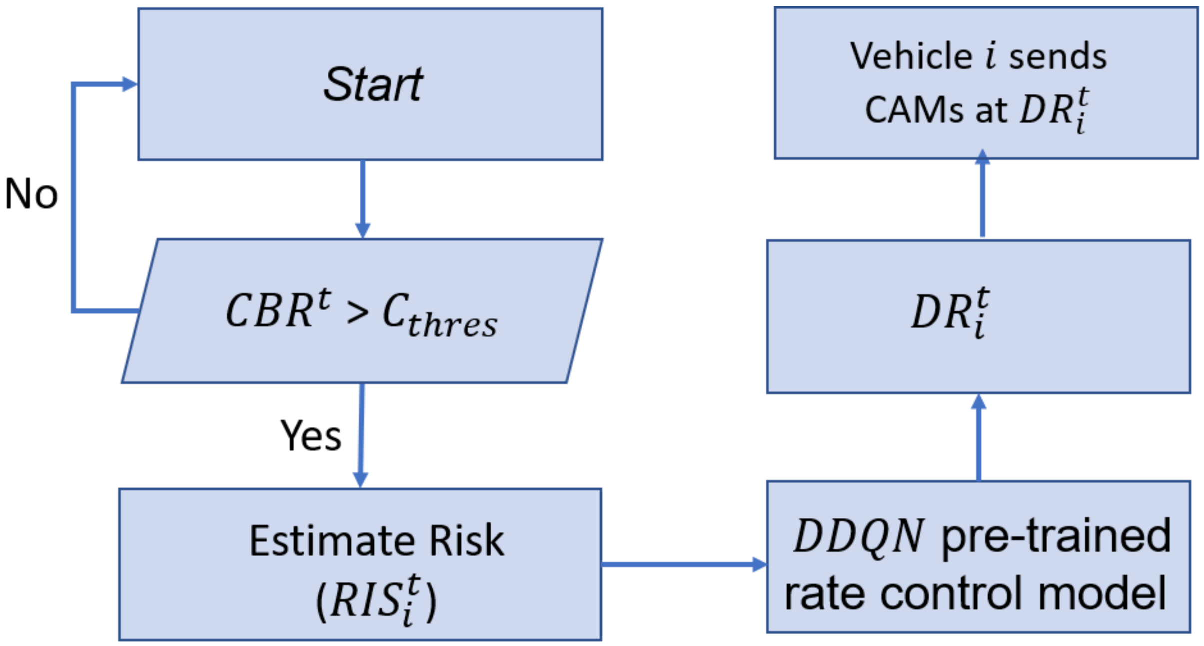
DDQN-based Transmission Control Algorithm

1. DDQN-based learning model is trained on the congested/heavy traffic cases in an offline training

2. Each vehicle is equipped with a pre-trained DDQN-based model

3. The DDQN-based rate control will adjust the sending rate DR_i^t based on its assessment on the channel (RIS, CBR) at the time t

Workflow



Source: our work [2]

Centralized vs Decentralized

Suitable for urban areas

- Centralized method: Road-side unit to play the role of data rate control

Advantage

- ✓ Fast learning convergence
- ✓ Easy to adjust hyperparameters

Disadvantage

- × Require centralized server connections (V2I), e.g., cloud server, road side units
- × Challenge to deploy in the areas without core network infrastructure

Suitable for rural areas

- Decentralized method: Vehicles negotiate with each other to determine the data rate

Advantage

- ✓ Work well with V2V environments

Disadvantage

- × Slower learning convergence
- × Difficult to maintain the consistency of learning models for vehicles with different computation capabilities.

Evaluation Results

Ours

Model	Meaning	Sending rate
DEEPCUT	▶DDQN-based rate control	Dynamic
RTC+ [24]	▶Time-to-collision rate control	Dynamic
DCC [12]	▶Channel busy ratio-based rate control	Dynamic
LIMERIC [14]	▶Channel busy ratio-based rate control	Dynamic

DSRC rate control

C-V2X/DSRC rate control

Adjust the broadcasting rate based on
the CBR level, regardless of risk/no-risk states

Simulator: Veins, OpenCV2X

System configuration

Parameter	Value	Parameter	Value
Batch-size	512	V2X frequency	5.9GHz
Number of episodes	2500	V2X bandwidth	20MHz
Experience replay	1024	Subcarrier spacing	30kHz
Discount factor γ	0.9	Access scheme	OFDMA
Hidden layers	256 neurons	Transmit power	25dBm
Learning rate	1-e4	Message size	300 bytes
Activation function	ReLU	Observation period	2s
Optimizer	ADAM	Number of antennas	4

Measurement Metric

- **Packet Delivery Rate**

→ the ratio of successfully received messages to the total number of messages sent

- **Channel Busy Ratio**

→ the ratio of time that the channel has been sensed busy in a given time window T

- **Collision risk**

→ the total times each pair of vehicles exceeds the safe distance at their relative speed

- **Computing time**

→ The latency of suggesting a proper broadcasting rate adjustment once the congestion occurs

- V2V communication standard
  1. IEEE 802.11p: 5.9GHz
  2. 5G C-V2X NR: 40GHz
- V2X communication scenario
  1. Heavy traffic (5-10 vehicles broadcasting)

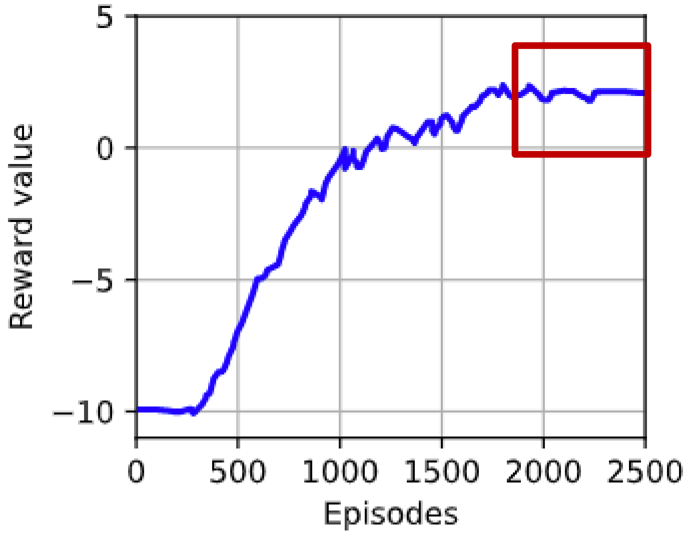
     → 200 vehicles/km
  2. Network congestion (> 20 vehicles broadcasting)

     → 300 vehicles/km

Luxembourg SUMO Traffic
(mobility model follows real traffic patterns)

Result – DDQN training

- The training converges after 2500 episodes
- If we set a high timestep and replay memory (large exploration), the training convergence is expected to be longer than this result



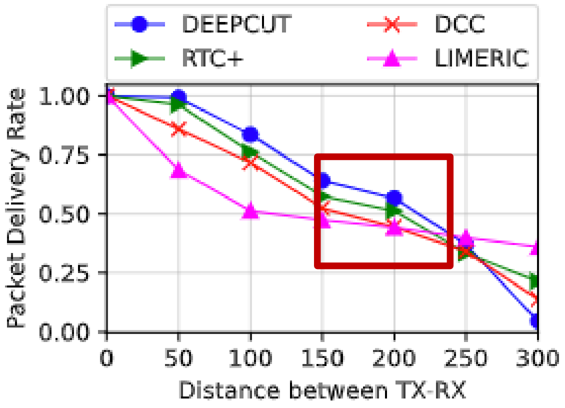
Source: from our work [2]

Packet Delivery Rate performance

- DEEPCUT yields 22.63% PDR performance better than DCC/LIMERIC with TX-RX distance < 200m

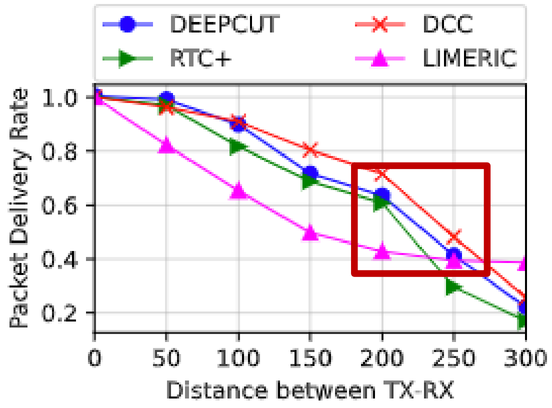
- If the TX-RX distance > 200m (far distance), collision risk is less critical → high cut + poor communication for far distance → low PDR but OK

- Advantage of DEEPCUT:
  - ✓ Hundreds of thousands of trial-and-fail training to find the best sending rate for multiple vehicle (multi-agent DRL)



(a)

Heavy traffic



(b)

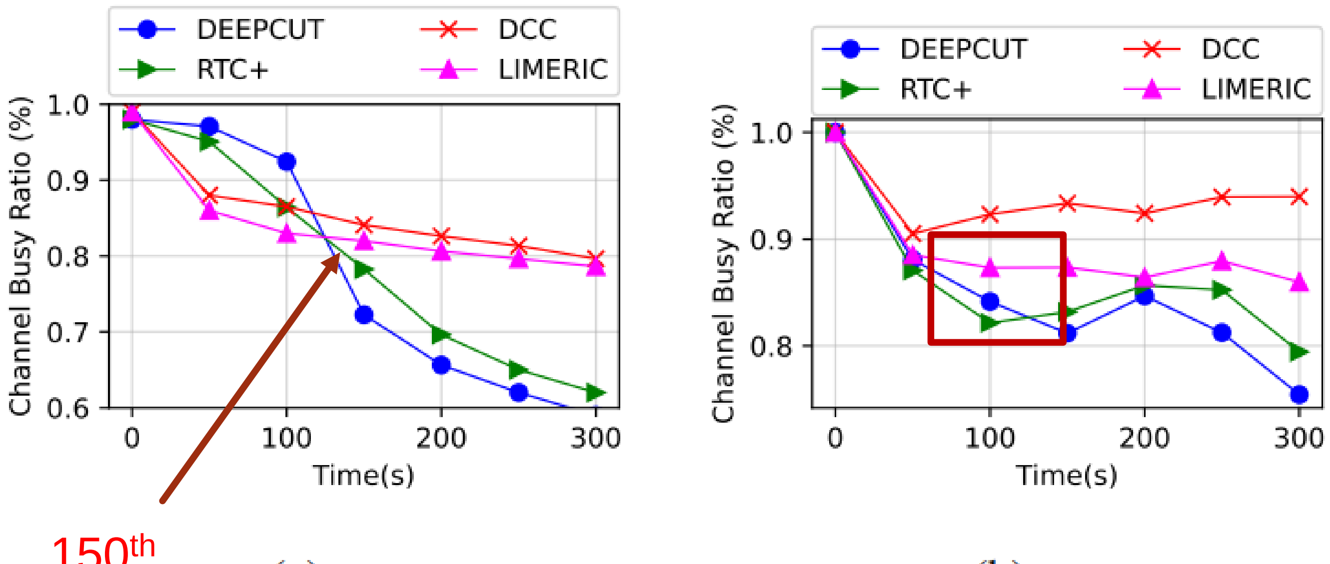
Congested channel

Source: from our work [2]

Channel Busy Ratio performance

- DEEPCUT maintains 20% better performance in overall CBR

- If traffic jam occurs (after 150th seconds), the risk of slow-moving vehicles is low → an aggressive rate control like ours can significantly reduce the CBR



(a)

Heavy traffic

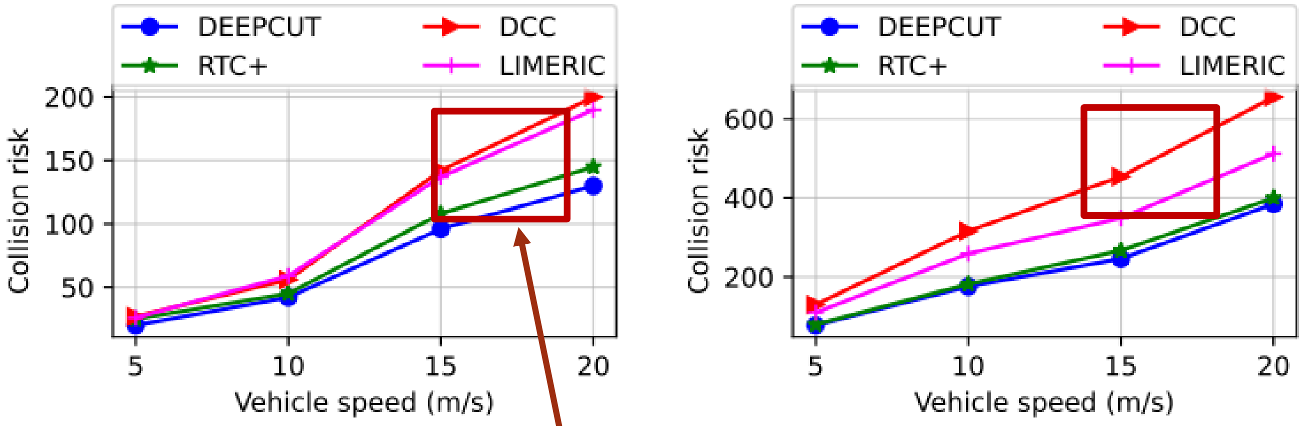
(b)

Congested channel

Source: from our work [2]

Collision risk performance

- DEEPCUT/RTC+ can reduce average 21% less collision risk in all the cases of traffic density
- Our risk-based assessment model contributed positive results
- Collision risk still occurs in some cases, if traffic jam or group vehicles moving near each others → we didn't control the vehicle behavior in this work



(a) Heavy traffic

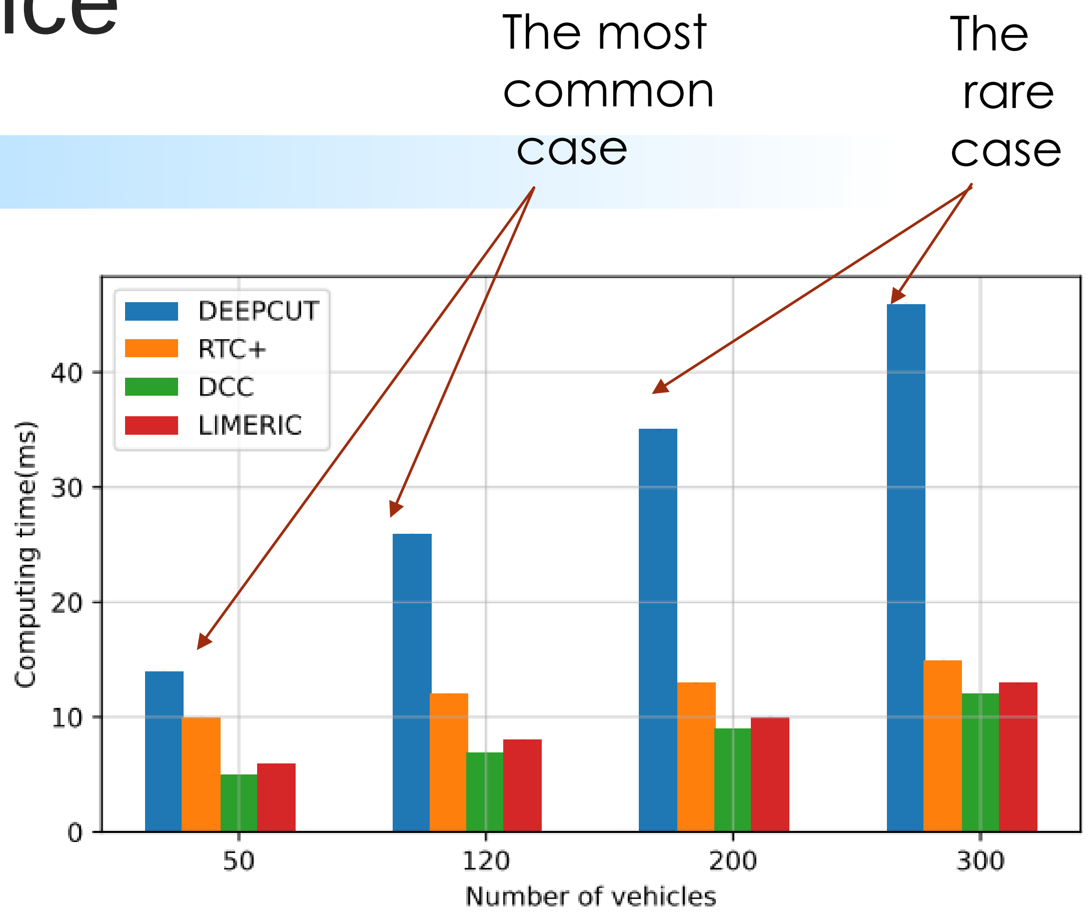
~21%

(b) Congested channel

Source: from our work [2]

Computing Time performance

- DEEPCUT gives the highest computing time, particularly to support many vehicles
  - ✓ Hard to find the consensus
  - ✓ Include the extensive computation (risk assessment)
- Computing time is still acceptable
  - ✓ Many V2X road-safety apps can accept latency *up to* 100ms [5]
  - ✓ In the future, computers in vehicles will be much stronger
  - ✓ The case of 300 vehicles per km is not common



Source: from our work [2]

Conclusion

- Two novel intelligent control schemes are efficient to resolve the channel congestion in V2V communications while still maintaining the safety proportionally.
- The risk factor is an advantage of our methods. It can help to the rate control to know exactly which vehicles should reduce the sending rate.
- Ongoing work: Support the fairness index in data rate control
- Future work: We move to support aerial vehicular communications, given their prospective to be deployed in 6G networks

Publication Overview

1. **Lan-Huong Nguyen**, Van-Linh Nguyen, and Jian-Jhih Kuo, "*Risk-Based Transmission Control for Mitigating Network Congestion in Vehicle-to-Everything Communications*," IEEE Access, vol. 9, pp. 144469-144480, Oct. 2021
2. **Lan-Huong Nguyen**, Van-Linh Nguyen, and Jian-Jhih Kuo, "*Efficient Reinforcement Learning-based Transmission Control for Mitigating Channel Congestion in 5G V2X Sidelink*," IEEE Access, vol. 10, pp. 62268 - 62281, Jun. 2022
3. **Lan-Huong Nguyen**, Ren-Hung Hwang, Po-Ching Lin, Van-Linh Nguyen, and Jian-Jhih Kuo, "*Robust Positioning-based Verification Scheme for Enhancing Reliability of Vehicle Platoon Control*," in IEEE Vehicular Technology Conference (VTC), Sep. 2021
4. Yun-Hao Ye, Zhi-Yang Lin, Chih-Chiung Yao, **Lan-Huong Nguyen**, Jian-Jhih Kuo, and Ren-Hung Hwang "*Efficient Multi-maneuver Platooning Framework for Autonomous Vehicles on Multi-lane Highways*" in IEEE Vehicular Technology Conference (VTC), Sep. 2021.
5. Van-Linh Nguyen, **Lan-Huong Nguyen**, Jian-Jhih Kuo, Po-Ching Lin, Ren-Hung Hwang "*Intelligent Aerial Relay Deployment for Enhancing Connectivity in Emergency Communications*," IEEE Transactions on Vehicular Technology (Major revision)
6. Van-Linh Nguyen, **Lan-Huong Nguyen,** Jian- Jhih Kuo, Ren-Hung Hwang, Po-Ching Lin," *Efficient Aerial Relaying Station Path Planning for Emergency Event-based Communications*", accepted to appear in IEEE CCNC 2023, Jan 2023.

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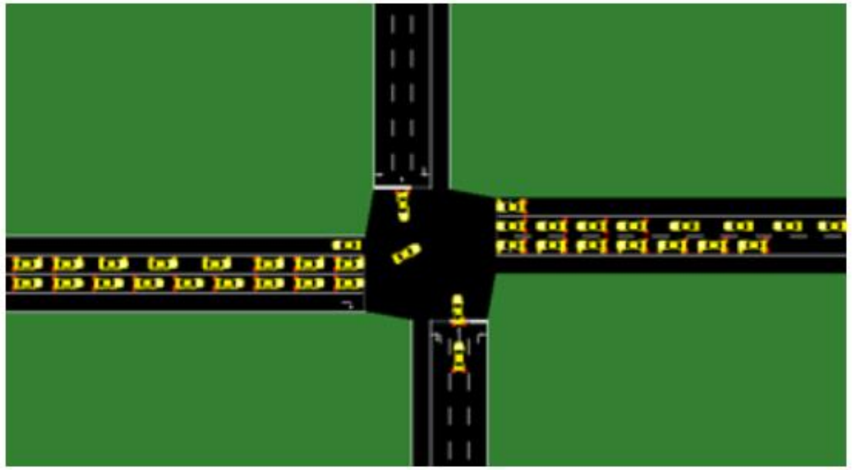
Thank you for listening!

Ongoing work

- If there are so many vehicles with the same risk assessment level, how to manage the fairness in cutting data for all vehicles?
- This part is addressed in our ongoing work which partially submitted to ICC 2023 for reviewing



(a) Platooning

(b) Mixed traffic case

Support fairness assessment factor

- We supply the fairness index
- Jain's fairness index J^t of data rate for all vehicles is defined as follows:

$$J^t = \frac{\left(\sum_i^N DR_i^t\right)^2}{N \sum_i^N (DR_i^t)^2} \quad (6)$$

This fairness index varies in accordance with the number of vehicles N and the achieved data rate. Given that multiple vehicles can be in the same group of high-risk/low-risk assessment, cutting the sending rate or lengthening the time interval for any vehicle should be flexibly adjusted to maintain the fairness of QoS gains for all vehicles of the group.

Rewritten problem statement

- The goal is to adjust the number of messages that transmit from N vehicles or the time interval for maximizing packet delivery rate of each vehicle PDR_i^t. This target is equal to the objective of the following optimization problem function

$$
\begin{aligned}
\underset{DR_i^t(S_i^t, T_i^t)}{\text{maximize}} \quad & \sum_{i \in N} PDR_i^t \qquad (7) \\
\text{subject to} \quad & DR_{i,j}^t \geq DR_{min}, \forall i \neq j \in \mathcal{N}, \forall t \in T \\
& CBR_i^t \leq 1, \forall t \in T \\
& RIS_{i,j}^t < 1, \forall i \neq j \in \mathcal{N}, \forall t \in T \\
& \boxed{J^t \geq J_{min}, \forall i \neq j \in \mathcal{N}, \forall t \in T}
\end{aligned}
$$

Update this constraint

Where J_{min} is the minimum Jain's fairness index value.

Updated Deep Reinforcement Learning

The problem of network congestion mitigation is equal to the objective of the following optimization problem function:

$$\underset{a_i^t}{\operatorname{argmax}} \sum_{k=0}^{\infty} \gamma^k \, r_i^{t+k} \qquad (8)$$

subject to

1. $DR_i^t \geq DR_{min},\, i \in [1, N], \forall\, t \in [0,1,..,T]$
2. $RIS_i^t < 1, i \in [1, N], \forall\, t \in [0,1,..,T]$
3. $\boxed{J^t \geq J_{min}\,, \forall\, t \in [0,1,..,T]}$

Update this constraint

where r_i^t is the reward for the action a_i^t

Some performance comparison (1/2)

- F-RTC : Fairness Risk-based Transmission Control

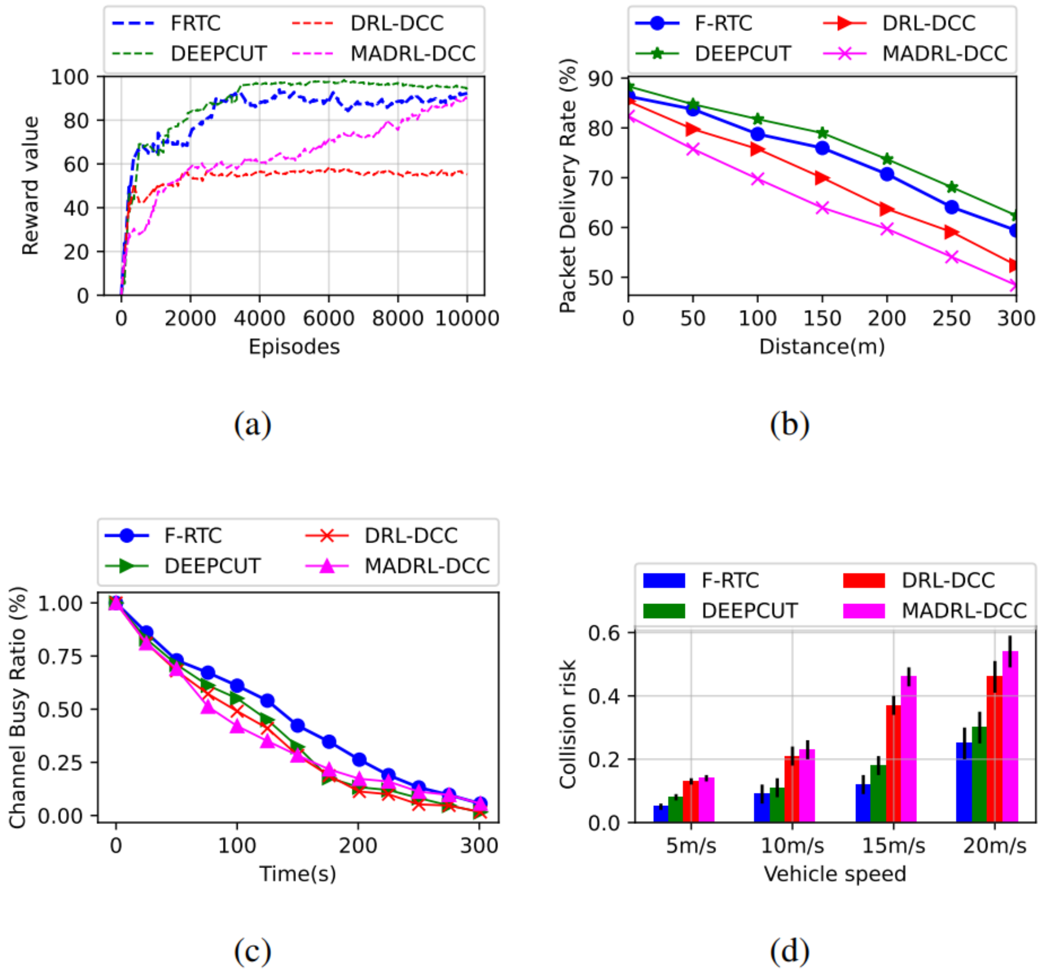
- Performance comparison

a) Reward accumulation

b) Packet Delivery Rate

c) Channel Busy Ratio

d) Collision risk



Some performance comparison (2/2)

- F-RTC : Fairness Risk-based Transmission Control
- F-RTC/DEEPCUT: 50-80ms
- Others: 90-120ms
- Shorter time interval is better