University of Modena and Reggio Emilia Department of Engineering "Enzo Ferrari"



Luca Lusvarghi and Maria Luisa Merani e-mail: *{luca.lusvarghi5, marialuisa.merani}@unimore.it*

Outline

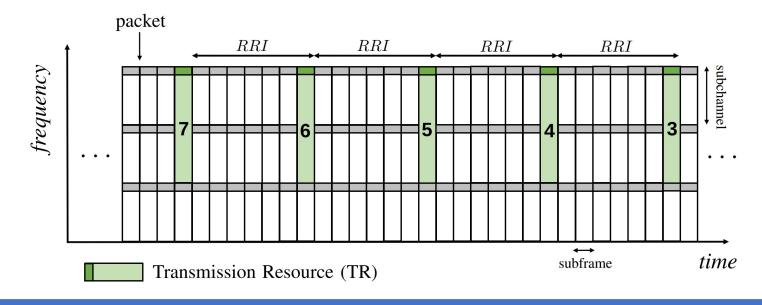


- Overview of LTE-V2X Mode 4
 - Impact of Aperiodic Traffic
- ETSI-generated CAMs
- Machine Learning to predict CAM Traffic
- Numerical Results
- Conclusions

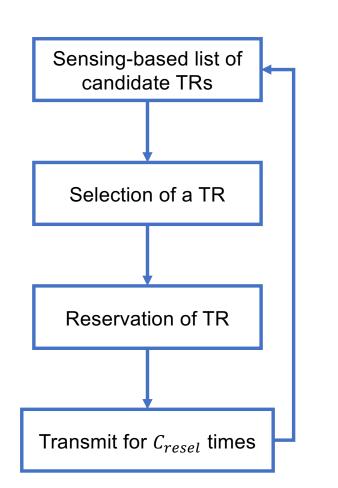
Overview of LTE-V2X Mode 4



- LTE-V2X is the current Cellular Vehicle-to-Everything (C-V2X) communication standard
 - Designed to support safety-oriented applications
 - Includes a distributed resource allocation mode known as Mode 4
 - In Mode 4, vehicles autonomously select and reserve Transmission Resources (TRs)
 - Contention-based approach



Overview of LTE-V2X Mode 4

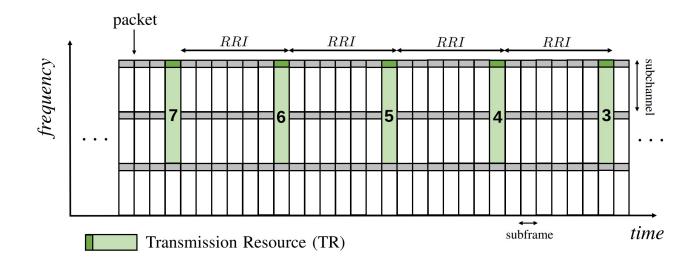


- Reservations of Transmission Resources (TRs) are periodic
 - Time between consecutive reservations:

Resource Reservation Interval (RRI)

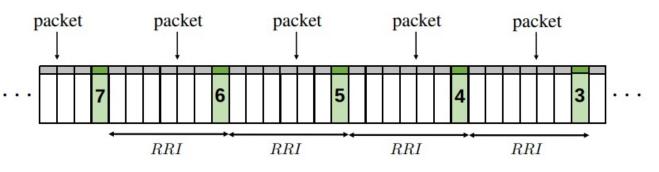
• Total number of reservations:

Reselection counter (Cresel)

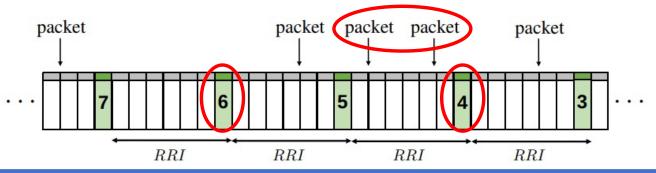


Impact of Aperiodic Traffic

- Periodic traffic:
 - RRI matches traffic periodicity



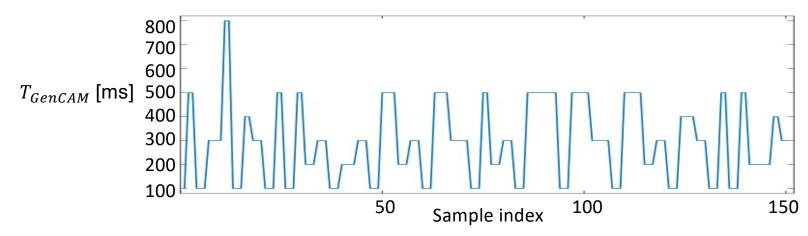
- Aperiodic traffic:
 - Inevitable mismatch between *RRI* and non-constant packet inter-arrival times
 - Drawbacks:
 - 1) Unused reservations
 - 2) Additional reselections



ETSI-generated CAMs



- LTE-V2X Mode 4 is designed to accommodate safety applications traffic
 - Such as Cooperative Awareness (CA) services standardized by ETSI
 - Information about the transmitting vehicle is broadcasted through
 - Cooperative Awareness Messages (CAMs)
- Yet, the CAMs inter-arrival time, *T_{GenCAM}*, depends on the generating **vehicle dynamics**:
 - 1. Position
 - 2. Speed
 - 3. Heading
- As a consequence, the generated traffic is aperiodic



Machine Learning to Predict CAM Traffic



- Can we minimize the number of unused reservations and additional reselections?
- The idea: dynamically adjust the resource reservation period in Mode 4
- How:
 - Use Machine Learning (ML) to predict future T_{GenCAM} values
 - Exploiting the strong correlation with the generating vehicle dynamics
 - Accordingly configure the *RRI* and *C*_{resel} parameters

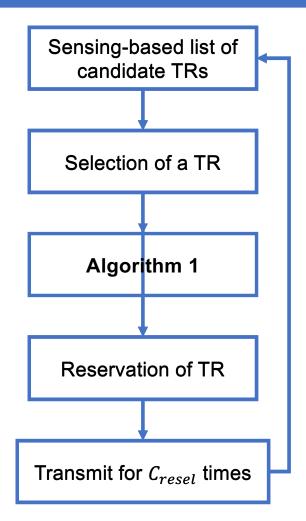
- Model the T_{GenCAM} prediction as a multi-class classification problem
- Use the K-Nearest Neighbors (KNN) algorithm
- Input features:
 - trajectory, speed and position of the generating vehicle
 - position and speed of the preceding vehicle

Machine Learning to Predict CAM Traffic



 A dedicated algorithm exploiting ML outputs the *RRI* and *C_{resel}* values used in the reservation phase

```
Algorithm 1: the proposed algorithm
Input : KNN input features
Output: RRI, C<sub>resel</sub>
i = 1:
T_{GenCAM_i} = Predict (Input features, i);
RRI = T_{GenCAM_i};
C_{resel} = 1;
while i < N do
   i = i + 1;
   T_{GenCAM_i} = Predict (Input features, i);
   if T_{GenCAM_i} = RRI then
       C_{resel} = C_{resel} + 1;
   else
       break:
   end
end
if C_{resel} > 3 then
   C_{resel} = random[3, C_{resel}]
end
```



Numerical Results: Simulation Environment

- Investigated scenario:
 - Extracted from Open Street Map (OSM) and simulated using SUMO
 - 2.5 km x 3 km area
 - 42 vehicles/km
 - Vehicles' speed ranging from [50,100] km/h

• LTE-V2X configuration:

Parameter	Values
Channel bandwidth	10 MHz
Number of subchannels	4
MCS	QPSK 0.7
Packet size	190, 470 bytes
Occupied subchannels	1 (190), 2 (470)

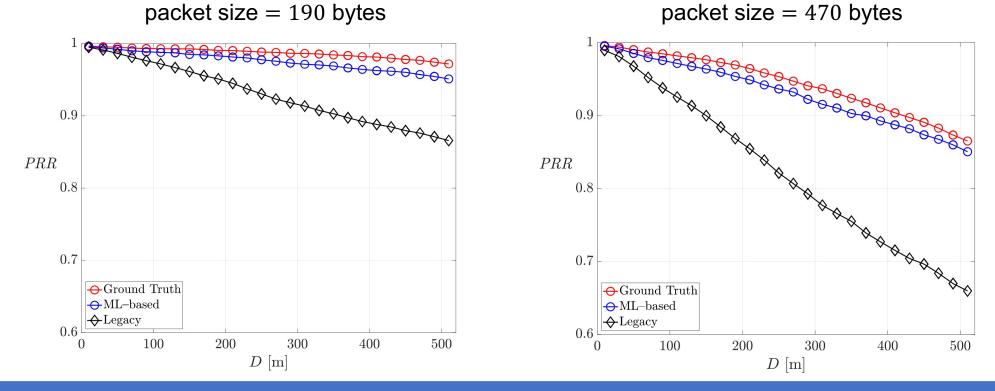




Numerical Results: Outcomes

Key Performance Indicator (KPI):

• Packet Reception Ratio (PRR): measures the fraction of vehicles successfully receiving a packet over the total number of intended receivers



Conclusions



- Presented a ML-based approach to distributed CAMs using LTE-V2X Mode 4
 - Based on a limited number of features
 - ➢ Using a simple KNN algorithm
- The ML-based solution outperforms legacy LTE-V2X Mode 4

THANK YOU FOR YOUR ATTENTION