Parallel and Successive Resource Allocation for V2V Communications in Overlapping Clusters

Luis F. Abanto-Leon

Co-authors: Arie Koppelaar
Sonia Heemstra de Groot

Department of Electrical Engineering
Eindhoven University of Technology

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Background

- In Release 14, 3GPP completed a first standard on C-V2X, where **vehicle–to–vehicle (V2V) mode-3**[1] was introduced.

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- Both *modes* are based on **device–to–device (D2D) communications** technology.

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Background

- In Release 14, 3GPP completed a first standard on C-V2X, where **vehicle–to–vehicle (V2V) mode-3**[1] was introduced.

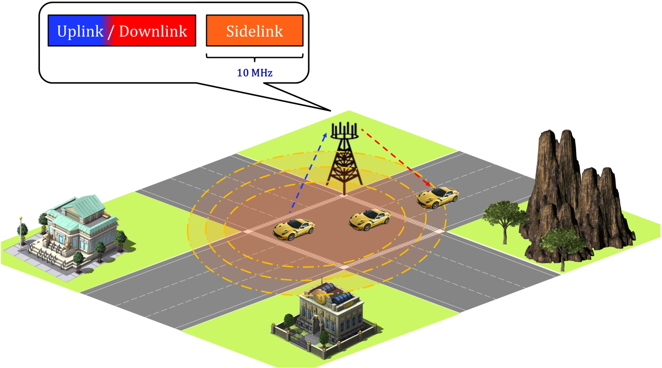
- Both *modes* are based on **device–to–device (D2D) communications** technology.

- Additional modifications have been applied to both *modes* in order to support more dynamic scenarios.

[1] V2V *mode-4* was also presented

Background

- Besides **uplink** and **downlink**, vehicles can also communicate via **sidelink** → direct communications.



V2V Mode-3 Operation

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  - Vehicles **communicate directly** via sidelink in a broadcast manner.

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  - eNodeBs **only** intervene in the **resource allocation** process.
  - Vehicles **communicate directly** via sidelink in a broadcast manner.
- In **safety** applications, vehicles exchange CAM messages.

V2V Mode-3 Operation (cont'd)

- Due to the broadcast nature of V2V *mode-3*, the resource allocation process differs from mainstream communications.

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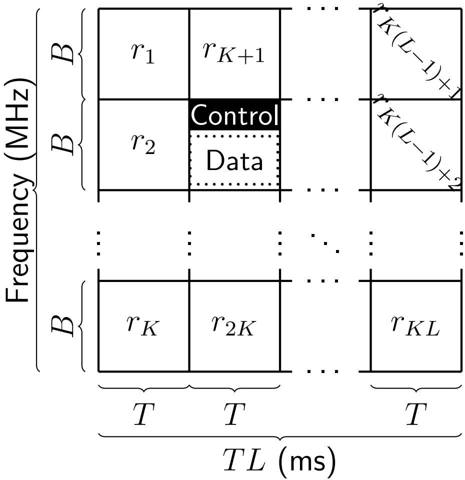
Example:

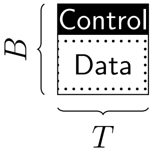
If two vehicles in mutual awareness range transmit concurrently they will not receive the message of the other.

Sidelink Channelization



- T: subframe duration
- K: subchannels per subframe
- L: available subframes for allocation
- B: subchannel bandwidth

Subchannel Structure



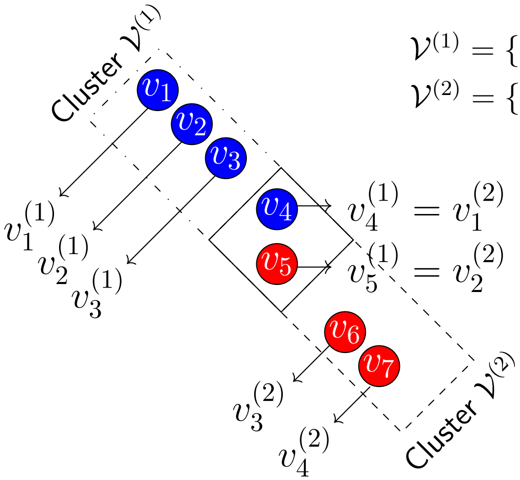
- B: 1.26 MHz
- T: 1 ms (2 slots of 0.5 ms each)
- Control: 2 RBs[2] per slot ← 24 subcarriers
- Data: 5 RBs per slot ← 60 subcarriers

Subchannel

We assume that 14 RBs can bear a payload of 200 bytes provided that eNodeBs can control power and MCS levels.

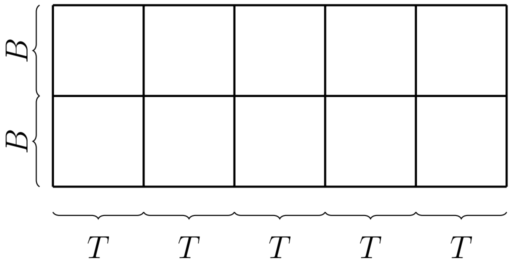
[2] RB: A resource block consists of 12 subcarriers

Motivation: Toy Example



$$\mathcal{V}^{(1)} = \{v_1, v_2, v_3, v_4, v_5\}$$
$$\mathcal{V}^{(2)} = \{v_4, v_5, v_6, v_7\}$$

Motivation: Toy Example



How can we accommodate the shown vehicles in the available subchannels?

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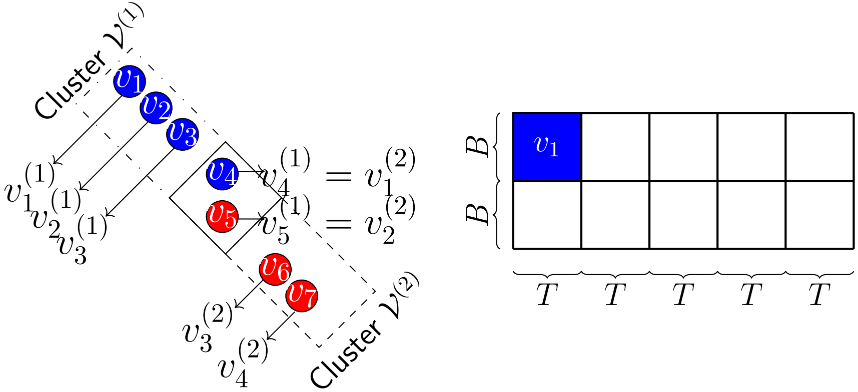

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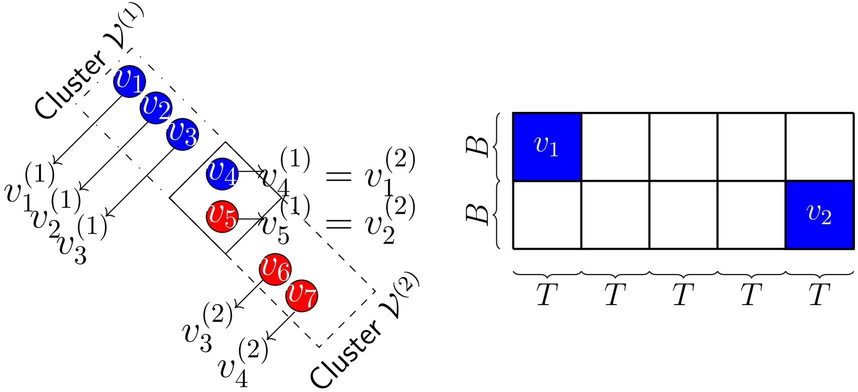

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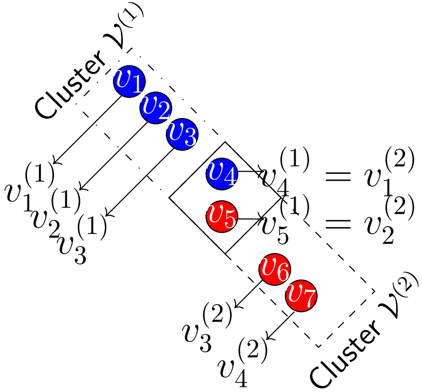

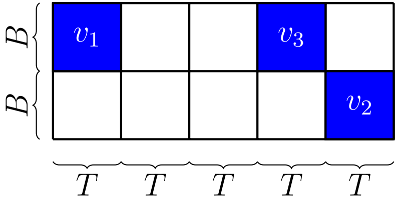

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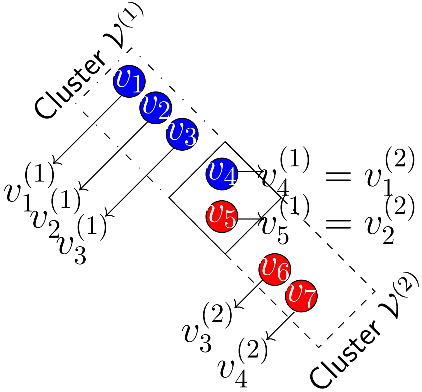

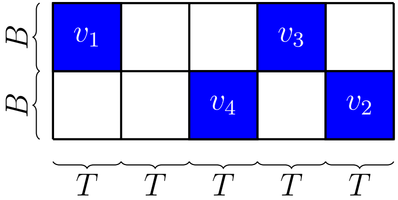

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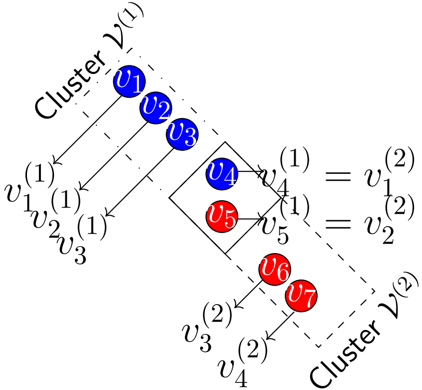

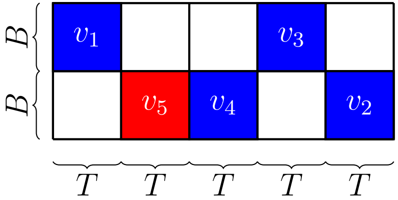

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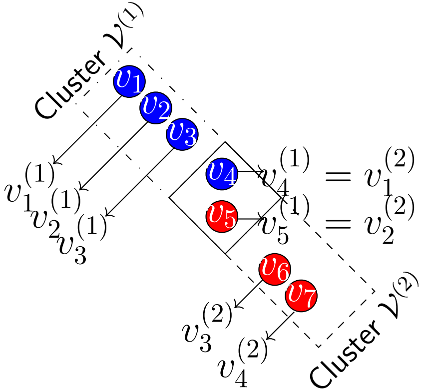

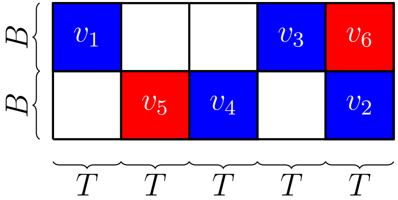

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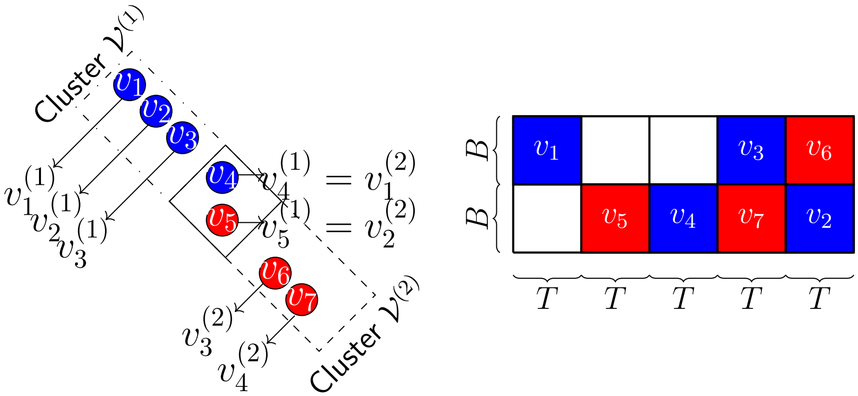

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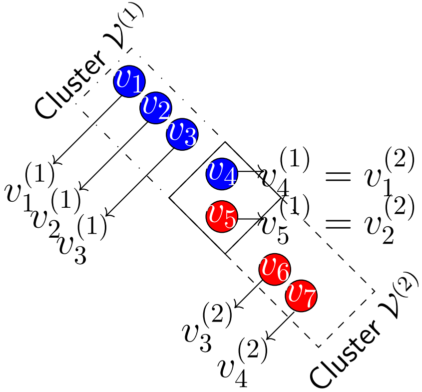
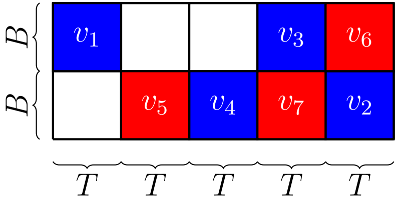




Problem Formulation

Identified Issues

- Vehicles can either transmit or receive at a time due to half-duplex PHY assumption.
- Concurrent transmissions in subchannels of the same subframe constitute a **conflict**.

Objectives

- Attain a **conflict-free subchannel assignment**.
- Maximize the sum-capacity of the system.

Problem Formulation (cont'd)

Identified Issues

- Vehicles can either transmit or receive at a time due to half-duplex PHY assumption.
- Concurrent transmissions in subchannels of the same subframe constitute a **conflict**.

Proposed Solutions

- Two approaches based on **bipartite graph matching**.
- Necessary constraints to **prevent conflicts** have been considered.

Problem Formulation (cont'd)

- For N vehicles and KL subchannels, a solution can be obtained upon solving

$$\max \mathbf{c}^T\mathbf{x}$$

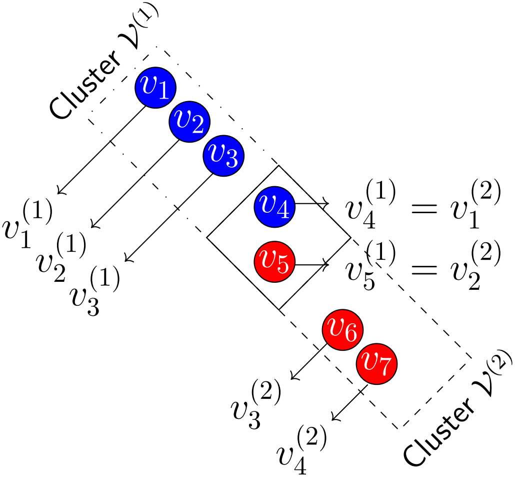
$$\text{subject to} \underbrace{\left(\begin{bmatrix} \mathbf{I}_{N\times N} \otimes \mathbf{1}_{1\times L} \\ \hline \mathbf{Q}_{J\times N} \otimes \mathbf{I}_{L\times L} \end{bmatrix} \otimes \mathbf{1}_{1\times K}\right)}_{\text{constraint matrix}} \mathbf{x} = \mathbf{1}$$

- However, this expression is complex to optimize.

Proposed Approaches

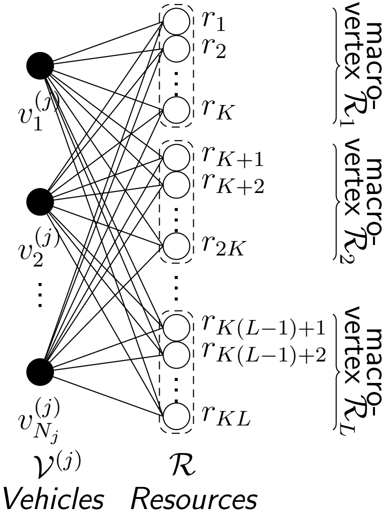
- We propose two approaches:
  - **BGM-SA:** bipartite graph matching-based successive allocation
  - **BGM-PA:** bipartite graph matching-based parallel allocation

BGM-SA



Cluster $\mathcal{V}^{(1)}$
v_1
v_2
v_3
v_4
v_5
v_6
v_7
$v_1^{(1)}$
$v_2^{(1)}$
$v_3^{(1)}$
$v_4^{(1)} = v_1^{(2)}$
$v_5^{(1)} = v_2^{(2)}$
$v_3^{(2)}$
$v_4^{(2)}$
Cluster $\mathcal{V}^{(2)}$

BGM-SA: Bipartite Graph



$$\max \sum_{i=1}^{N_j} \sum_{k=1}^{KL} c_{ik} x_{ik}$$

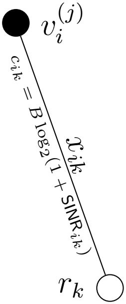
subject to

$$\sum_{k=1}^{KL} x_{ik} = 1, \quad i = 1, \dots, N_j$$

$$\sum_{i=1}^{N_j} \sum_{k \in \mathcal{R}_\alpha} x_{ik} = 1, \quad \alpha = 1, \dots, L$$

$$x_{ik} = \{0, 1\}.$$

BGM-SA: Optimization Problem



The optimization problem can be recast as:

$$\max\ \mathbf{c}_j^T \mathbf{x}_j$$

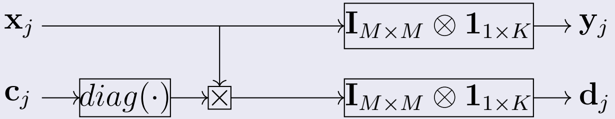
$$\text{subject to}\ \underbrace{\left(\begin{bmatrix} \mathbf{I}_{N_j \times N_j} \otimes \mathbf{1}_{1\times L} \\ \hline \mathbf{1}_{1\times N_j} \otimes \mathbf{I}_{L\times L} \end{bmatrix} \otimes \mathbf{1}_{1\times K} \right)}_{\text{constraint matrix}} \mathbf{x}_j = \mathbf{1}$$

$$\mathbf{x}_j = [x_{1,1}^{(j)}, \ldots, x_{1,KL}^{(j)}, \ldots, x_{L,1}^{(j)}, \ldots, x_{L,KL}^{(j)}]^T$$
$$\mathbf{c}_j = [c_{1,1}^{(j)}, \ldots, c_{1,KL}^{(j)}, \ldots, c_{L,1}^{(j)}, \ldots, c_{L,KL}^{(j)}]^T.$$

Note: For completeness, $N = L$.

BGM-SA: Transformation

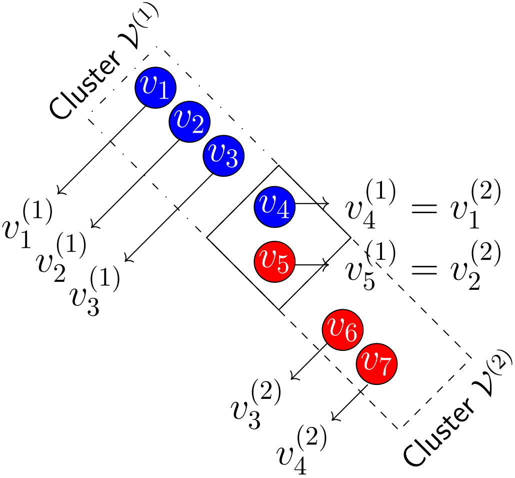
Transformation



$$\max \; \mathbf{d}_j^T \mathbf{y}_j$$
$$\text{subject to} \; \left[\frac{\mathbf{I}_{L\times L} \otimes \mathbf{1}_{1\times L}}{\mathbf{1}_{1\times L} \otimes \mathbf{I}_{L\times L}}\right] \mathbf{y}_j = \mathbf{1}$$

This problem can be approached via Kuhn-Munkres algorithm.

BGM-PA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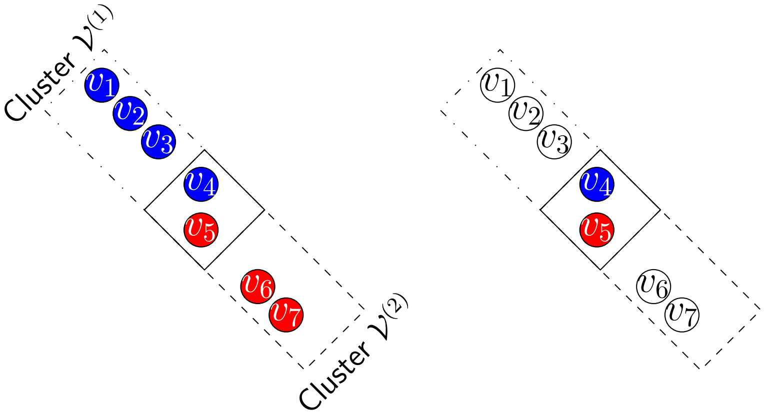
Cluster $\mathcal{V}^{(2)}$

BGM-PA: Random Pre-grouping



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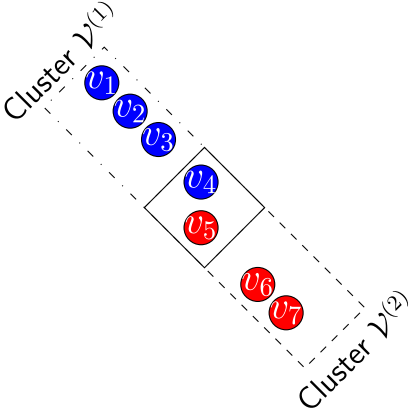

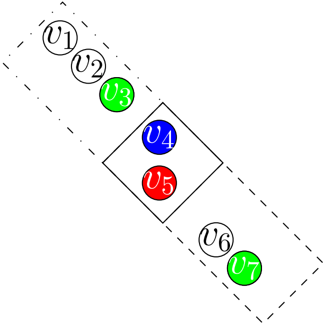

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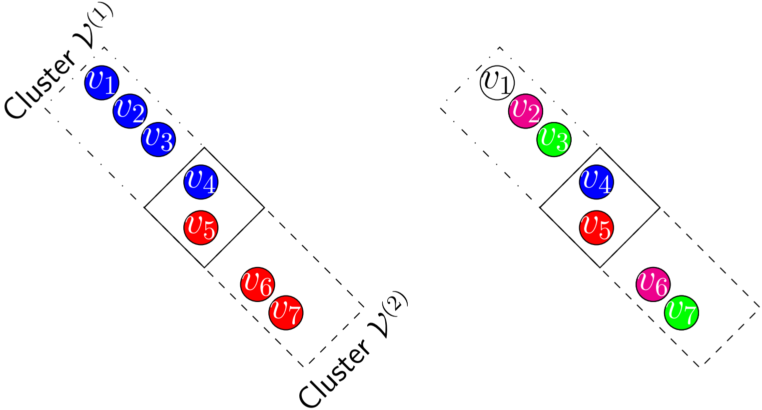

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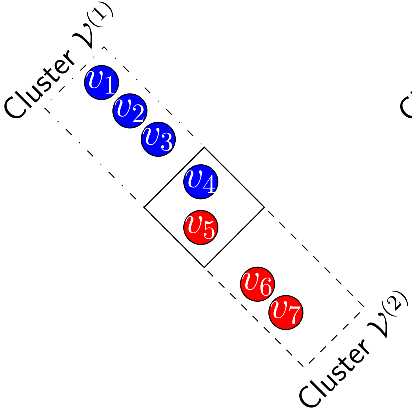

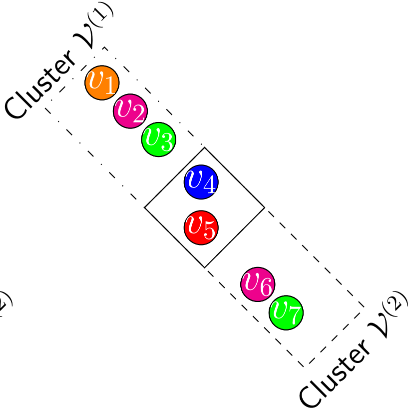

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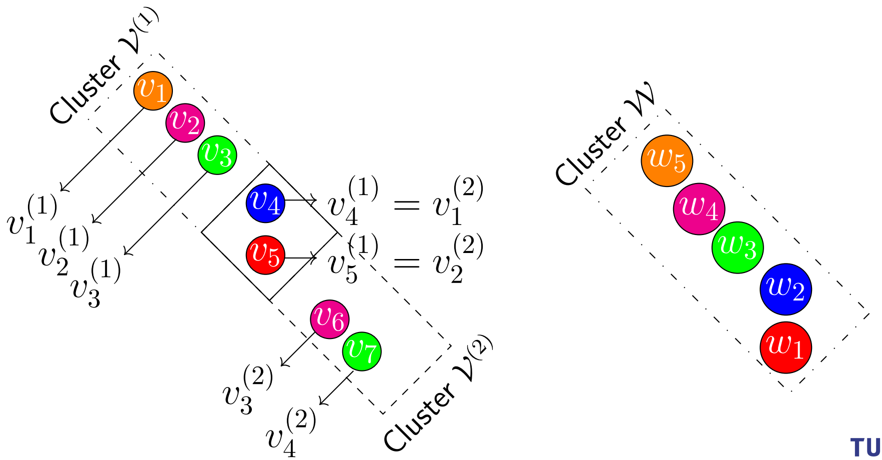

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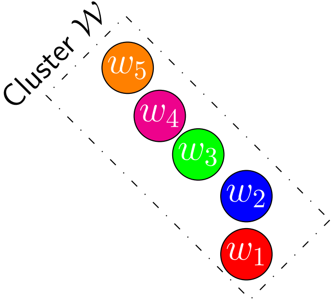
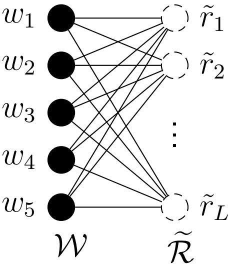




BGM-PA: Matching

But, what criterion should we use for matching?

- Minimum (MIN) → BGM-PA-MIN
- Maximum (MAX) → BGM-PA-MAX
- Average (AVE) → BGM-PA-AVE
- Inverse of variance (IVAR) → BGM-PA-IVAR
- Minimum plus maximum (MPM) → BGM-PA-MPM
- Combined metrics (COMB) → BGM-PA-COMB
  COMB = AVE + MIN - $\sqrt{VAR}$

Simulations: Data Rate per Vehicle

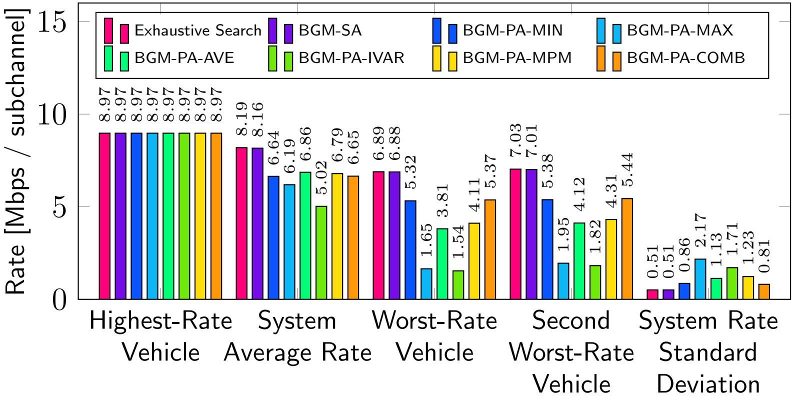


Figure 1: Data rate for $N = 210, L = 100$ and $K = 7$ with $J = 3, N_1 = 100, N_2 = 90, N_3 = 80, \hat{N} = 30$

Simulations: Least Favored Vehicle

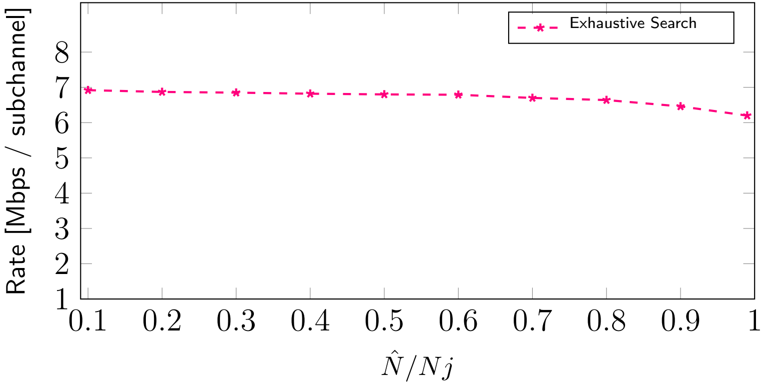
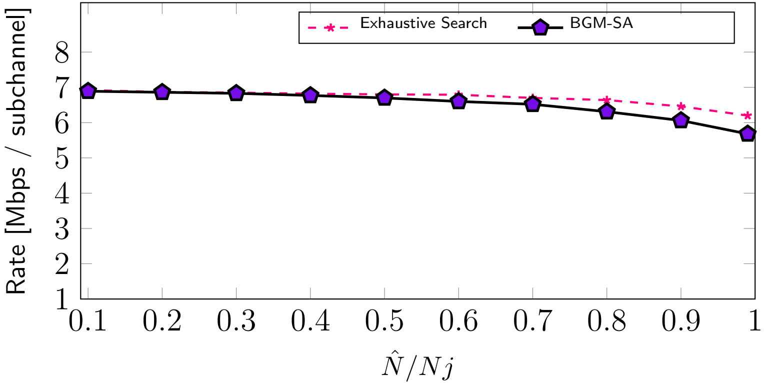


Figure 2: Worst-rate vehicle for $L = 100, K = 7$ with $J = 4, N_1 = 100, N_2 = 100, N_3 = 100, N_4 = 100$ and varying $\hat{N}$.

Simulations: Least Favored Vehicle



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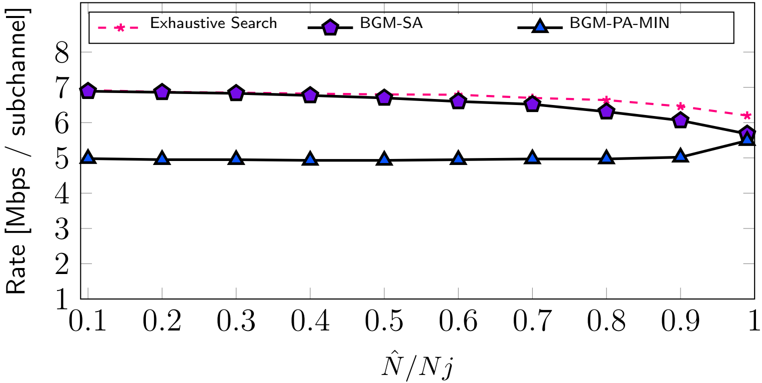

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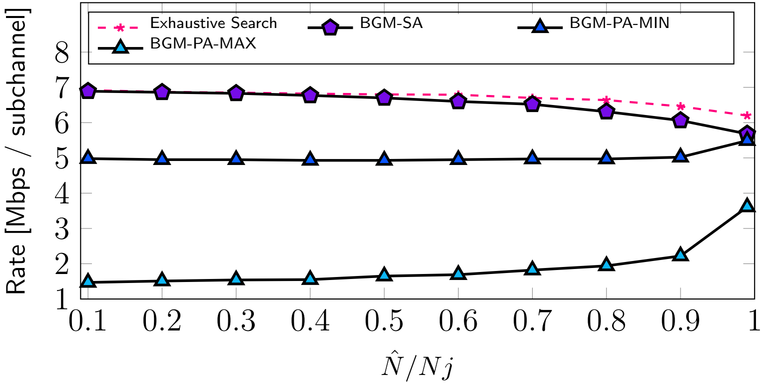

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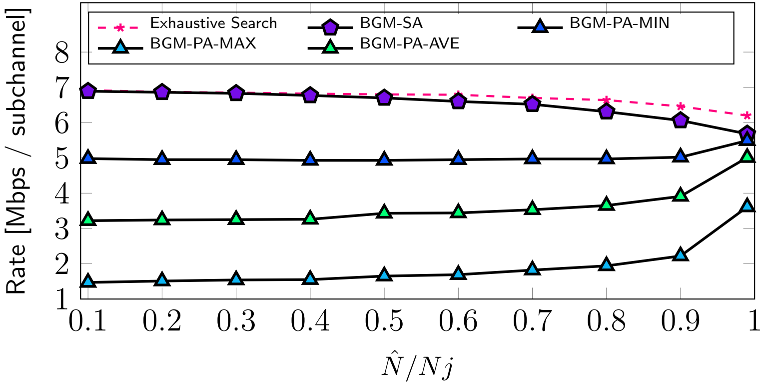

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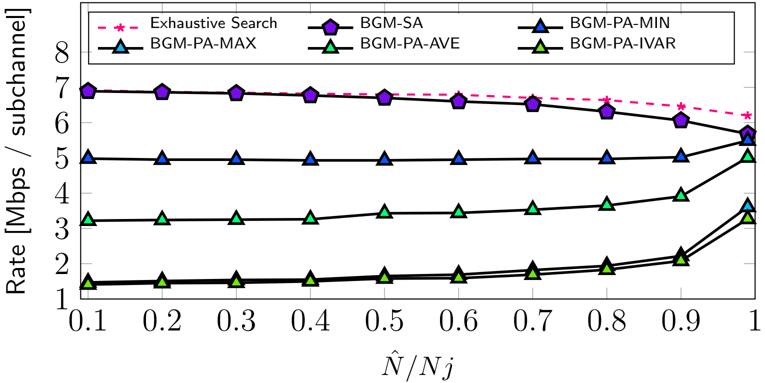

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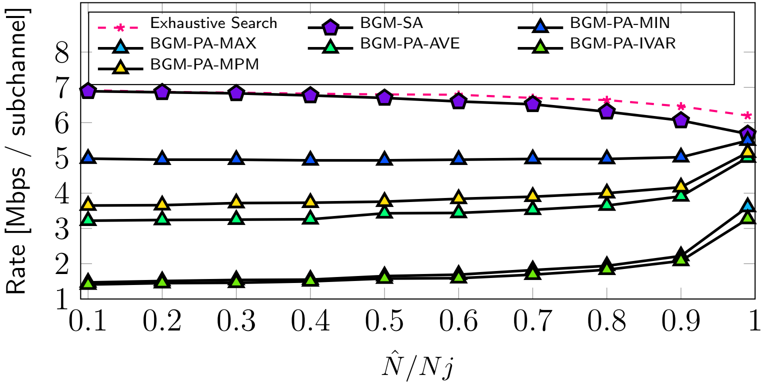

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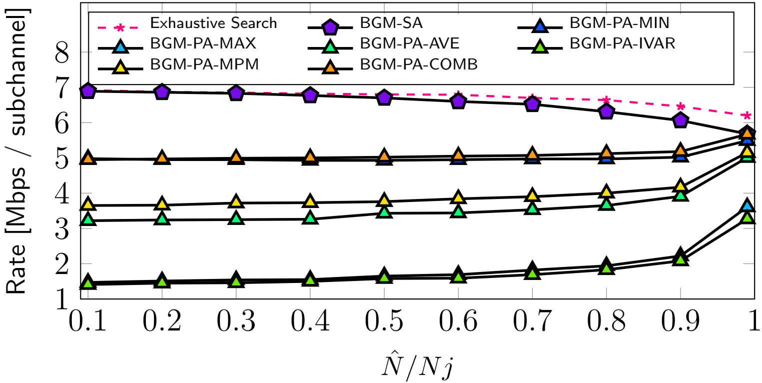

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Conclusions

- Two approaches for V2V *mode-3* were presented.
- We identified a trade-off between performance and complexity in the proposed approaches.
- Six metrics for representing the channel conditions of a group of vehicles were presented.
- The number of vehicles at the intersection impacts on the performance of the proposed methods.

Questions

Optimization Problem

Objective Function

$\max \mathbf{c}^T \mathbf{x}$

Because $\mathbf{x} \in \mathbb{B}^{MK}$, then the objective function can be recast as

$$\mathbf{c}^T \mathbf{x} \equiv \mathbf{x}^T diag(\mathbf{c}) \mathbf{x}$$

without affecting optimality.

Note that $M = N^2$.

Optimization Problem

Objective Function

$\max \ \mathbf{c}^T \mathbf{x}$

For any vehicle v_i,

$$x_{ij}x_{ik} = 0, \ r_j, r_k \in \mathcal{R}_\alpha.$$

Moreover,

$$c_{ij}x_{ij}x_{ik} = 0, \ r_j, r_k \in \mathcal{R}_\alpha.$$

In general, for N vehicles

$$\mathbf{x}^T \left(\mathbf{I}_{M \times M} \otimes [\mathbf{1}_{K \times K} - \mathbf{I}_{K \times K}] \right) diag(\mathbf{c})\mathbf{x} = 0.$$

Optimization Problem

Objective Function

$\max \ \mathbf{c}^T\mathbf{x}$

As long as $\mathbf{x}^T\left(\mathbf{I}_{M\times M} \otimes [\mathbf{1}_{K\times K} - \mathbf{I}_{K\times K}]\right) diag(\mathbf{c})\mathbf{x} = 0$ holds, conflicts will be prevented.

We can aggregate this condition to the objective function. Hence,

$$\mathbf{c}^T\mathbf{x} = \mathbf{x}^T diag(\mathbf{c})\mathbf{x} + \mathbf{x}^T\left(\mathbf{I}_{M\times M} \otimes [\mathbf{1}_{K\times K} - \mathbf{I}_{K\times K}]\right) diag(\mathbf{c})\mathbf{x}$$

Further manipulation leads to

$$\mathbf{c}^T\mathbf{x} = \mathbf{x}^T(\mathbf{I}_{M\times M} \otimes \mathbf{1}_{K\times K}) diag(\mathbf{c})\mathbf{x}$$

Optimization Problem

Objective Function

$\max \mathbf{c}^T\mathbf{x}$

Property 1 (Product of two tensor products)
Let $\mathbf{X} \in \mathbb{R}^{m\times n}$, $\mathbf{Y} \in \mathbb{R}^{r\times s}$, $\mathbf{W} \in \mathbb{R}^{n\times p}$, and $\mathbf{Z} \in \mathbb{R}^{s\times t}$, then

$$\mathbf{XY} \otimes \mathbf{WZ} = (\mathbf{X} \otimes \mathbf{W})(\mathbf{Y} \otimes \mathbf{Z}) \in \mathbb{R}^{mr\times pt}$$

$$\begin{aligned}
\mathbf{c}^T\mathbf{x} &= \mathbf{x}^T(\mathbf{I}_{M\times M} \otimes \mathbf{1}_{K\times K})diag(\mathbf{c})\mathbf{x} \\
&= \mathbf{x}^T(\mathbf{I}_{M\times M}\mathbf{I}_{M\times M} \otimes \mathbf{1}_{K\times 1}\mathbf{1}_{1\times K})diag(\mathbf{c})\mathbf{x} \\
&= \underbrace{\mathbf{x}^T(\mathbf{I}_{M\times M} \otimes \mathbf{1}_{K\times 1})}_{\mathbf{y}^T}\underbrace{(\mathbf{I}_{M\times M} \otimes \mathbf{1}_{1\times K})diag(\mathbf{c})\mathbf{x}}_{\mathbf{d}}
\end{aligned}$$

Optimization Problem

Constraints

$$\text{subject to} \left[\frac{\mathbf{I}_{N\times N} \otimes \mathbf{1}_{1\times N}}{\mathbf{1}_{1\times N} \otimes \mathbf{I}_{N\times N}}\right] \otimes \mathbf{1}_{1\times K}\ \mathbf{x} = \mathbf{1}$$

Property 2 (Pseudo-inverse of a tensor product)

Let $\mathbf{X} \in \mathbb{R}^{m\times n}$ and $\mathbf{Y} \in \mathbb{R}^{r\times s}$, then

$$(\mathbf{X} \otimes \mathbf{Y})^{\dagger} = \mathbf{X}^{\dagger} \otimes \mathbf{Y}^{\dagger} \in \mathbb{R}^{ns\times mr}$$

Optimization Problem

Constraints

$$\text{subject to} \begin{bmatrix} \mathbf{I}_{N\times N} \otimes \mathbf{1}_{1\times N} \\ \hline \mathbf{1}_{1\times N} \otimes \mathbf{I}_{N\times N} \end{bmatrix} \otimes \mathbf{1}_{1\times K} \ \mathbf{x} = \mathbf{1}$$

$$\left(\begin{bmatrix} \mathbf{I}_{N\times N} \otimes \mathbf{1}_{1\times N} \\ \hline \mathbf{1}_{1\times N} \otimes \mathbf{I}_{N\times N} \end{bmatrix} \otimes \mathbf{1}_{1\times K} \right) \left(\mathbf{I}_{M\times M} \otimes \mathbf{1}^{\dagger}_{1\times K} \right) \mathbf{y} = \mathbf{1}$$

$$= \left(\begin{bmatrix} \mathbf{I}_{N\times N} \otimes \mathbf{1}_{1\times N} \\ \hline \mathbf{1}_{1\times N} \otimes \mathbf{I}_{N\times N} \end{bmatrix} \mathbf{I}_{M\times M} \right) \otimes \underbrace{\left(\mathbf{1}_{1\times K} \mathbf{1}^{\dagger}_{1\times K} \right)}_{1} \mathbf{y} = \mathbf{1}$$

$$= \begin{bmatrix} \mathbf{I}_{N\times N} \otimes \mathbf{1}_{1\times N} \\ \hline \mathbf{1}_{1\times N} \otimes \mathbf{I}_{N\times N} \end{bmatrix} \mathbf{y} = \mathbf{1}$$

Optimization Problem

Original Problem

$$\max \mathbf{c}^T\mathbf{x}, \quad \text{subject to} \left[\frac{\mathbf{I}_{N\times N} \otimes \mathbf{1}_{1\times N}}{\mathbf{1}_{1\times N} \otimes \mathbf{I}_{N\times N}}\right] \otimes \mathbf{1}_{1\times K}\ \mathbf{x} = \mathbf{1}$$

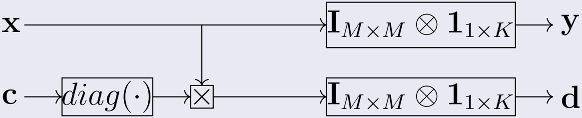
Resultant Problem

$$\max \mathbf{d}^T\mathbf{y}, \qquad \text{subject to} \left[\frac{\mathbf{I}_{N\times N} \otimes \mathbf{1}_{1\times N}}{\mathbf{1}_{1\times N} \otimes \mathbf{I}_{N\times N}}\right]\mathbf{y} = \mathbf{1}.$$

where $\mathbf{d} = (\mathbf{I}_{M\times M} \otimes \mathbf{1}_{1\times K})diag(\mathbf{c})\mathbf{x}$ and
$\mathbf{y} = (\mathbf{I}_{M\times M} \otimes \mathbf{1}_{1\times K})\mathbf{x}$
Dimensionality reduction: $\rightarrow |\mathbf{x}| = MK \quad \rightarrow |\mathbf{y}| = M$.
The resultant problem can now be approached through the Kuhn-Munkres Algorithm

Optimization Problem

Transformation



$$\mathbf{d} = \lim_{\beta\to\infty} \frac{1}{\beta} \overset{\circ}{\log}\left\{(\mathbf{I}_{M\times M} \otimes \mathbf{1}_{1\times K})\mathrm{e}^{\circ\beta\mathbf{c}}\right\}$$

$\overset{\circ}{\log}\{\cdot\}$: Element-wise natural logarithm.

$\mathrm{e}^{\circ\{\cdot\}}$ Hadamard exponential.

Simulations: CDF

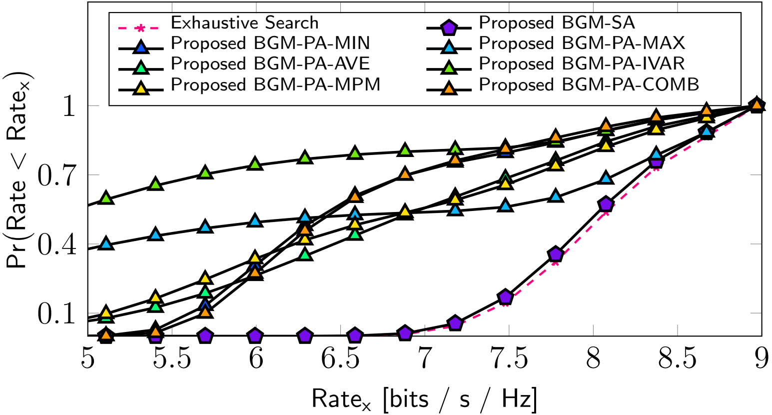


Figure 3: CDF of rate values for $L = 100, K = 7$ with $J = 3, N_1 = 100, N_2 = 90, N_3 = 80$ and $\hat{N} = 50$.

Simulations: Data Rate per Vehicle

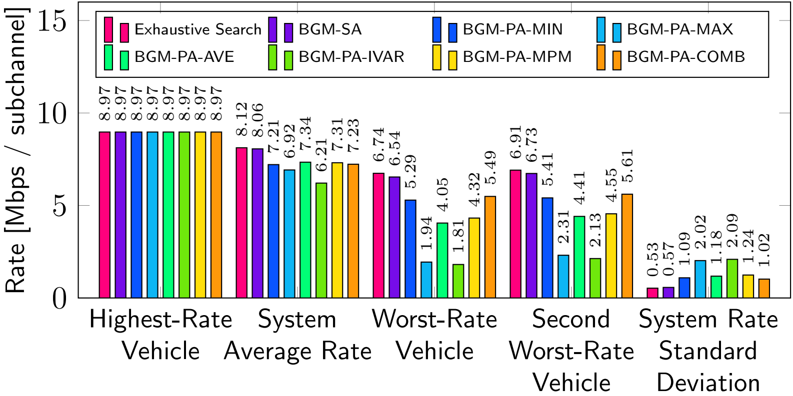


Figure 4: Data rate for $N = 130, L = 100$ and $K = 7$ with $J = 3, N_1 = 100, N_2 = 90, N_3 = 80, \hat{N} = 70$