Constrained Control of Multi-Vehicle Systems for Smart Cities and Industry 4.0: from Model Predictive Control to Reinforcement Learning
Part 4 - Distributed control architecture: a joint distributed reinforcement learning and model predictive control approach

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DIMEG

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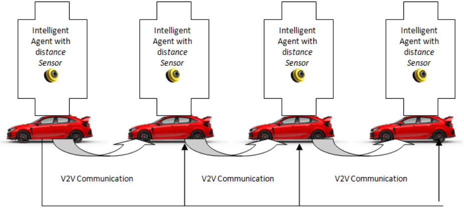
Aim

Autonomous vehicles in urban road networks -

Develop an efficient path planning strategy for constrained autonomous vehicles moving in the cluttered environments of urban road networks under time-varying operating scenarios

Multi-vehicle configuration -

The autonomous vehicles are topologically organized as a platoon



Key aspects -

- the computation of routing decisions for mitigating traffic congestion phenomena
- a constrained control strategy in charge of adequately exploiting the routing decisions

Problem statement (1/3)

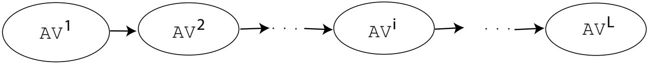
Modeling -

- Topological configuration: Platoon of L autonomous vehicles
- Dynamics:

$$x^i(t+1) = A^i x^i(t) + B^i u^i(t), \;\; i = 1, \ldots, L,$$

  - $x^i(t) = [p^i(t)^T, \, {x_{np}^i}^T]^T$: $x_{np}^i \in \mathbb{R}^{n_i - 2}$ accounts for the non-spatial components
  - $u^i \in \mathbb{R}^{m_i}$: the control input
- Set-membership constraints:

$$\begin{aligned} x^i(t) \in \quad & \mathcal{X}^i := \{x^i \in \mathbb{R}^{n_i} : {x^i}^T x^i \leq \bar{x}^2\}, \\ u^i(t) \in \quad & \mathcal{U}^i := \{u^i \in \mathbb{R}^{m_i} : {u^i}^T u^i \leq \bar{u}^2\}, \;\; \forall t \geq 0, \bar{x}, \, \bar{u} \in \mathbb{R}^+ \end{aligned}$$

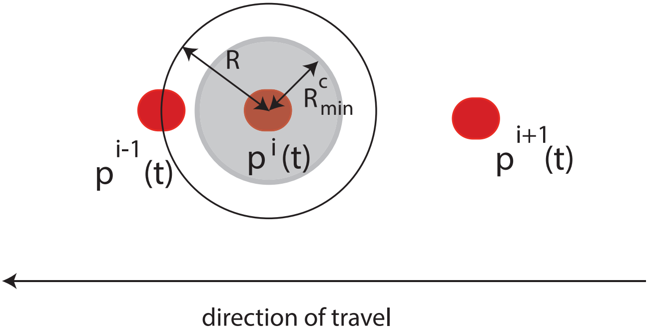


Problem statement (2/3)

Perception capabilities -

- vehicles are equipped with a **perception module** with a detection radius $R > 0$
- **field of view**: 360^o
- **minimum curvature radius**: $R > R^c_{min}$

Detected region: the ball $\mathcal{B}(p^i(t), R)$ centered at the current vehicle planar position $p^i(t)$



Problem statement (3/3)

Information exchange -

At each t, AV^i sends to AV^{i+1} its predicted future state trajectory $\hat{\mathbf{x}}^i(t)$

Operating scenario -

- **Link**: a portion of a road comprised between two junctions
- **Urban road network**: M links and F junctions, where sequence of routing decisions have to be taken into account during the travel

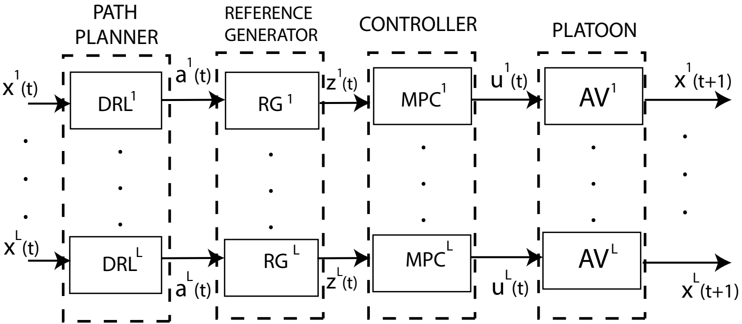
Platoons in Urban Environments (PL-UE) -

Given a platoon of constrained autonomous vehicles and a target $x_f = [{x_f^1}^T, {x_f^2}^T, \ldots, {x_f^L}^T]^T$, design a distributed state-feedback control policy

$$\begin{array}{rcl} u^1(t) & = & g(x^1(t), x_f^1), \\ u^i(t) & = & g(x^i(t), \hat{\mathbf{x}}^{i-1}(t), x_f^i), \qquad i = 2, \ldots, L, \end{array}$$

satisfying state and input constraints and such that, starting from an admissible initial condition $x(0) = [{x^1}^T(0), {x^2}^T(0), \ldots, {x^L}^T(0)]^T$, the team is driven towards x_f regardless any junction occurrence

Proposed solution: an overview



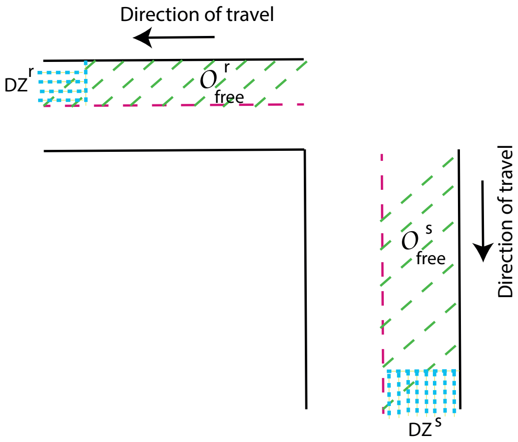
Basic units -

- Path Planner : based on distributed reinforcement learning arguments, **receives** the measurement $x^i(t)$ and **generates** the action $a^i(t)$ (link road selection) to be executed by the vehicle AV^i until the next junction
- Reference Generator : **translates** $a^i(t)$ into a set-point $z^i(t)$ for the underlying control logic
- Controller : **computes** an admissible command $u^i(t)$ in a distributed receding horizon fashion

Urban Road Network (1/2)

Characterizing aspects -

- the environment is *a-priori* known, i.e., the link-free region $\mathcal{O}^j_{free}$
- a decision zone DZ^j is defined for each link:$H^j p > b^j, p \in \mathbb{R}^2$,



Customization -

- Geometric constraints:

$$(\mathcal{X}_c)^i_j \triangleq \mathcal{X}^i \cap \mathcal{O}^j_{free} := \{x^i \in \mathbb{R}^{n_i} : {x^i}^T x^i \le \bar{x}_j^2\} \; i = 1, \ldots, L, \; j = 1, \ldots, M$$

- Set-point computation:

$$z^i(t) := \arg \max_{z^i \in (\mathcal{X}_c)^i_{a^i(t)}} \|x^i(t) - z^i\|^2$$

Decision zone -

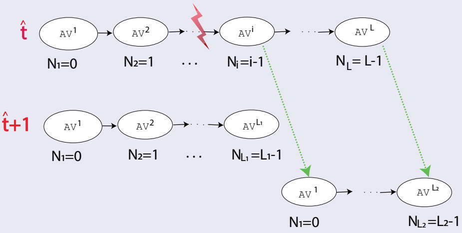
Exploited for routing decision purposes

Model Predictive Controllers -

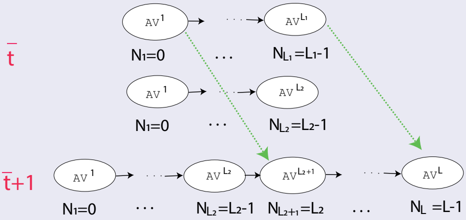
1. the leader AV^1 implements a receding horizon controller with $N_1 = 0$
2. each follower AV^i uses an MPC controller with $N_i = i-1, i = 2, \dots, L$

Time-varying leader-follower topology -

The current platoon can be split in two or more leader-follower configurations



Two platoons LF^1 and LF^2 can be grouped by reconnecting the leader of LF^1 to the leaf node of LF^2



Distributed Reinforcement learning scheme

Task -

The routing problem is recast as a path search on a connected graph by exploiting as a threshold the decision zone

Vehicle density -

Given a road link j, the vehicle density is

$$\rho^j(t) \triangleq \frac{\mu^j(t)}{\bar{d}^j l^j}$$

with $\mu^j(t) \in \mathbb{Z}^+$ the number of vehicles on the link j, $\bar{d}^j \in \mathbb{R}^+$ the average road width and l^j the road length

Multi-agent RL model -

$$< V, \Sigma, \Lambda, \Phi >$$

- $V = \{AV^1, \ldots, AV^h\}$: the set of vehicles
- $\Sigma := \{\sigma^i\}_{i=1}^h$: the set of RL states
- Λ : the admissible vehicle actions: e.g., “turn right”, “turn left”, “go straight on”;
- $\Phi : \Sigma \times \Lambda \times \Sigma \rightarrow \mathbb{R}$: the global reward function

DMPC units: single platoon (1/7)

Notation -

- $x^i(t+k|t)$, $u^i(t+k|t)$: $k-th$ predicted state and predicted control
- $\mathbf{x}^i(t) := \{x^i(t+k|t)\}_{k=0}^{N_i}$, $\mathbf{u}^i(t) := \{u^i(t+k|t)\}_{k=0}^{N_i}$: predicted state and predicted control sequences
- $\mathbf{x}^{i^*}(t) := \{x^{i^*}(t+k|t)\}_{k=0}^{N_i}$: optimal state trajectory
- $\hat{\mathbf{x}}^i(t) := \{\hat{x}^i(t+k|t)\}_{k=0}^{N_i}$: assumed state trajectory

Information exchange -

The sequence $\hat{\mathbf{x}}^i$ is transmitted to AV^{i+1} which in turn hypothesizes that AV^i will implement during the update prediction time interval

$$[(t+1)+k,\ (t+1)+k+N_i]$$

DMPC units: single platoon (2/7)

Ingredients -

- Input sequence parametrization:

$$u^i(\cdot|t) = \begin{cases} u^i(t+k|t), & k = 0, \ldots, N_i - 1 \\ K^i x^i(t+k|t), & k \geq N_i \end{cases}$$

  with $K^i \in \mathbb{R}^{m_i \times n_i}$

- Cost-to-go:

$$J^i(x(t|t), x^i_f, \mathbf{u}^i(t)) := \sum_{k=t}^{t+N_i-1} \left[\|x^i(t+k|t) - x^i_f\|^2_{R^i_x} + \|u^i(t+k|t)\|^2_{R^i_u} \right] + \|x^i(t+N_i|t) - x^i_f\|^2_{P^i}$$

  with $R^i_x = R^{i^T}_x > 0$, $R^i_u = R^{i^T}_u \geq 0$, $P^i = P^{i^T} \geq 0$

- Terminal constraint:

$$x^i(t+N_i|t) \in \Xi^i \subset \mathbb{R}^{n_i}$$

Positively invariance -

The pair (Ξ^i, K^i) is such that $u^i(\cdot) = K^i x^i(\cdot)$ a **stabilizing** state feedback law and Ξ^i a **positively invariant** region for the state evolutions of the closed-loop system:

$$x^i(t+N_i|t) \in \Xi^i \Rightarrow (A^i + B^i K^i)^{t+N_i+k} x^i(t+N_i|t) \in \Xi^i, \forall k \geq 0$$

DMPC units: single platoon (3/7)

Time-varying terminal sets -

- the LF formation moves towards x_f
- the vehicle must take into account routing decisions $z^i(t)$ at each junction

Prescriptions -

- Given the equilibrium $\bar{x}^i_{t-1}$, the positively invariant region $\Xi^i(t)$ is such that

$$\bar{x}^i_{t-1} \in \Xi^i(t-1) \cap \Xi^i(t)$$

- Terminal set-membership requirement:

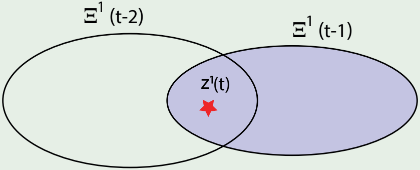
$$x^i(t+N_i|t) \in \Xi^i(t-1) \cup \Xi^i(t)$$

- Leader admissible set constraint:

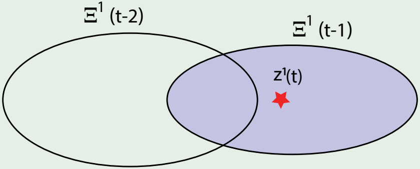
$$\text{Proj}_p(\Xi^1(t)) \subseteq \mathcal{B}(p^1(t), R), \forall t \geq 0$$

- Follower admissible sets: $\Xi^i(t)$, $i \geq 2$, take advantage of transmitted $\Xi^{i-1}(t-1)$

Leader positively invariant set computation -

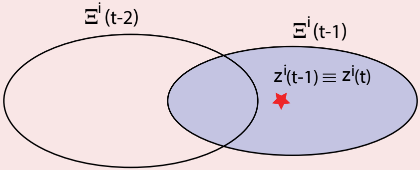


$$\begin{cases} \Xi^1(t) := \arg\min_{\Xi^1} \, dist(x_f^1, \Xi^1) \;\; \text{s.t.} \\ \bar{x}^1_{t-1} \in \Xi^1(t-1) \cap \Xi^i(t) \\ \text{Proj}_p(\Xi^1(t)) \subseteq \mathcal{B}(p^1(t), R), \forall t \geq 0 \end{cases}$$

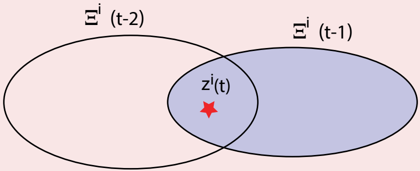


$$\begin{cases} \Xi^1(t) := \arg\min_{\Xi^1} \, dist(z^1(t), \Xi^1) \;\; \text{s.t.} \\ \bar{x}^i_{t-1} \in \Xi^1(t-1) \cap \Xi^1(t) \\ \text{Proj}_p(\Xi^1(t)) \subseteq \mathcal{B}(p^1(t), R), \forall t \geq 0 \end{cases}$$

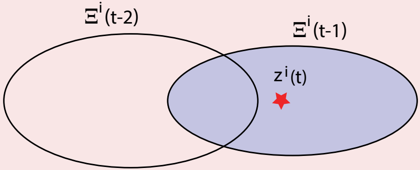
Follower positively invariant set computation -



$$\begin{cases} \Xi^i(t) := \arg\min_{\Xi^i} dist(\Xi^i, \Xi^{i-1}(t-1)) \text{ s.t.} \\ \bar{x}^i_{t-1} \in \Xi^i(t-1) \cap \Xi^i(t) \end{cases}$$



$$\begin{cases} \Xi^i(t) := \arg\min_{\Xi^i} dist(x^i_f, \Xi^i) \text{ s.t.} \\ \bar{x}^i_{t-1} \in \Xi^i(t-1) \cap \Xi^i(t) \end{cases}$$



$$\begin{cases} \Xi^i(t) := \arg\min_{\Xi^i} dist(z^i(t), \Xi^i) \text{ s.t.} \\ \bar{x}^i_{t-1} \in \Xi^i(t-1) \cap \Xi^i(t) \end{cases}$$

Predecessor assumed state sequence -

Given

- the current state condition: $x^i(t|t) \in \mathcal{X}^i$
- the received optimal state sequence of AV^{i-1} at the previous time instant $t-1$: $\mathbf{x}^{(i-1)^*}(t-1)$

The vehicle AV^i will implement

$$\hat{\mathbf{x}}^{i-1}(t) = \begin{cases} x^{(i-1)^*}(t-1+k|t-1), k = 1, \ldots, N_{i-1} \\ (A^{i-1} + B^{i-1}K^{i-1})^{t-1+k} x^{(i-1)^*}(t-1+N_{i-1}|t-1), k = N_{i-1}+1, \ldots, N_i \end{cases}$$

Formation constraints -

- Preserve the platoon configuration
- Maintain a safe distance from a vehicle and its predecessor
- Requirements in terms of desired relative distance and bearing between AV^i and AV^{i-1}

Leader optimization problem - $\mathcal{P}_L(t)$:

$$\min_{K^1,\Xi^1} \sum_{k=t}^{\infty}\left[\|x^1(t+k|t)-x^1_f\|^2_{R^1_x}+\|u^1(t+k|t)\|^2_{R^1_u}\right] \text{ subject to}$$

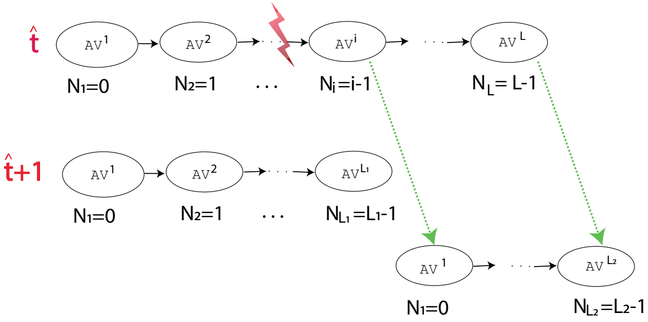
$$x^1(t+k+1|t)=A^1x^1(t+k|t)+B^1u^1(t+k|t),\ \forall k \quad - \quad \text{Dynamics}$$
$$u^1(t+k|t)=K^1x^1(t+k+1|t)\in\mathcal{U}^1,\ \forall k \quad - \quad \text{Saturation}$$
$$x^1(t+k|t)\in\mathcal{X}^1,\ \forall k \quad - \quad \text{Geometric}$$
$$\bar{x}^1_{t-1}\in\Xi^1(t-1)\cap\Xi^1(t) \quad - \quad \text{Terminal set}$$

Follower optimization problem - $\mathcal{P}^i_F(t)$:

$$\min_{\mathbf{u^i(t)}} J^i(x(t|t),x^i_f,\mathbf{u}^i(t)) \text{ subject to}$$

$$x^i(t+k+1|t)=A^ix^i(t+k|t)+B^iu^i(t+k|t) \quad - \quad \text{Dynamics}$$
$$u^i(t+k|t)\in\mathcal{U}^i,\ k=0,1,\ldots,N_i-1 \quad - \quad \text{Saturation}$$
$$x^i(t+k|t)\in\mathcal{X}^i,\ k=0,1,\ldots,N_i-1 \quad - \quad \text{Geometric}$$
$$x^i(t+N_i|t)\in\Xi^i(t) \quad - \quad \text{Terminal set}$$
$$\alpha^c_{min}\le\|p^i(t+k|t)-\hat{p}^{i-1}(t+k|t)\|\le\alpha^c_{max},\ k=0,1,\ldots,N_i \quad - \quad \text{Formation}$$

$\alpha^c_{max}\in\mathbb{R}^+$ and α^c_{min} are guaranteed bounds depending on formation requirements



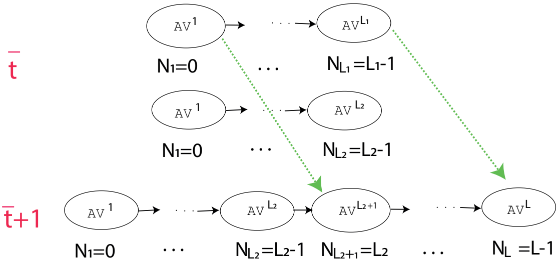
Modus operandi -

- At $\hat{t}$, the routing decision sequence $\{a^1(\hat{t}), a^2(\hat{t}), \ldots, a^L(\hat{t})\}$ is such that

$$\exists i : a^k(\hat{t}) \neq a^{k+1}(\hat{t}), \quad k = i, \ldots, L-1$$

- Two platoon configurations: LF^1 and LF^2 :
  - LF^1 keeps the same control horizon lengths $N_i = i-1, i = 1 \ldots, L_1$
  - LF^2 modifies the control horizon length as $N_{L_2} = 0, \ N_i = i - L_2, \ i = L_2 + 1, \ldots, L$
  - A *re-numbering* procedure is implemented: $\{AV_i^1\}_{i=1}^{L_1}$ and $\{AV_i^2\}_{i=1}^{L_2}$

Platoon queuing



Modus operandi -

- LF^1 is added to LF^2 or *viceversa* at the leaf node of the first platoon
- horizon lengths are set as $N_h = N_{L_1} + h$, $h = 1, \dots, L_2$

Leaf node detection -

- AV^i makes available a data packet $Count^i = \{Count^i.child(i), Count^i.N_i\}$, the integer $child(i)$ accounts for its follower: $child(i) = 0$ implies no follower
- $Count^i$ can be acquired by AV^h if $\alpha^c_{min} \leq \|p^h(\bar{t}) - p^i(\bar{t})\|_2 \leq \alpha^c_{max}$

Regrouping -

LF^1 platoon is able to regroup with LF^2 when $Count^{L^2}$ is detected by AV^1 of LF^1

SUMO *versus* MATLAB co-design (1/2)

Simulation of **U**rban **MO**bility®(SUMO) -

- Open source highly portable, microscopic and continuous multi-modal traffic simulation package
- Handle large urban road networks
- Traffic is described by means of departure times and routes with certain duration
- Particularly suitable to simulate different classes of vehicles: cars, trains,buses
- Simulation engine is based on an hybrid description : discrete-time and continuous-space.
- Enjoy collision avoidance capabilities, multi-lane roads under lane changing, junction-based right-of-way rules, lane-to-lane connections
- Data expressed in XML formats

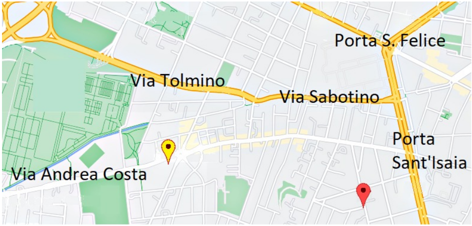
Ingredients -

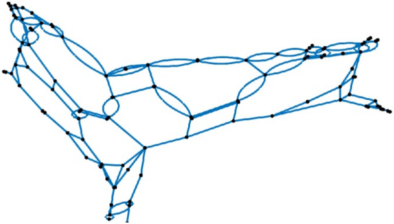
- The TraCI4Matlab®toolbox allowing the communication between any MATLAB application and the SUMO traffic simulator
- The TraCI application level protocol is based on the client-server paradigm
- The application developed in MATLAB plays the role of a client and it can access and modify the simulation environment provided by SUMO that acts as a server

SUMO *versus* MATLAB co-design (2/2)

Co-design procedure -

- Urban road network information are properly encoded into MATLAB objects
- A MATLAB graph is obtained by exploiting SUMO XML files: junctions (nodes), roads (edges)
- A set of APIs get, modify or add information about vehicles within the simulation environment
- Neural network weights optimization by the MATLAB Reinforcement Learning toolbox® and the MATLAB Deep learning toolbox®





Simulation setup -

- Matlab R2022a environment by using the SUMO 1.11.0 toolbox
- Lenovo IdeaPad L340-15RH laptop equipped with an Intel Core i9 processor under a $64-$bit operating system

Vehicle platoon and constraints -

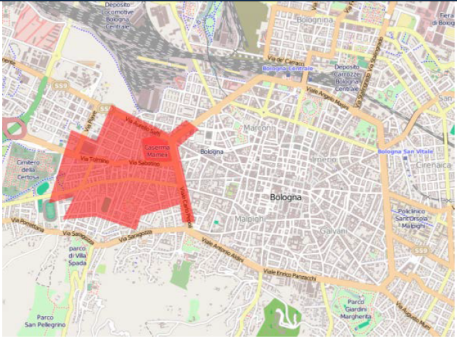
- Platoon: $L = 11$ vehicles
- Point mobile robot dynamics:
  - $x^i = [p_x^i,\ p_y^i,\ v_x^i,\ v_y^i]^T$: (p_x^i, p_y^i) the vehicle planar coordinates and (v_x^i, v_y^i) velocity components
  - $u_i = [a_x^i,\ a_y^i]^T \in \mathbb{R}^2$ the acceleration vector
  - $$A^i = \begin{bmatrix} I_2 & T_s I_2 \\ 0_2 & I_2 \end{bmatrix},\ B^i = \begin{bmatrix} \frac{T_s^2}{2} I_2 \\ T_s I_2 \end{bmatrix},$$
  - $T_s = 1\,[s]$ the sampling time
  - Input constraints
    $$\|u^i(t)\|^2 \leq 5\,[m/s^2],\ \forall t \geq 0$$
  - Formation constraints
    $$\alpha_{min}^c \leq \|p^i(t+k|t) - \hat{p}^{i-1}(t+k|t)\| \leq \alpha_{max}^c,\ \alpha_{min}^c = 3\,[m],\ \alpha_{max}^c = 10\,[m]$$

Simulations (2/12)

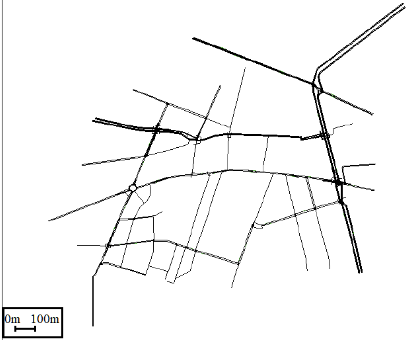
Urban road network -

The district around the “Andrea Costa” road in Bologna (IT)

Bologna Map



SUMO Road Network



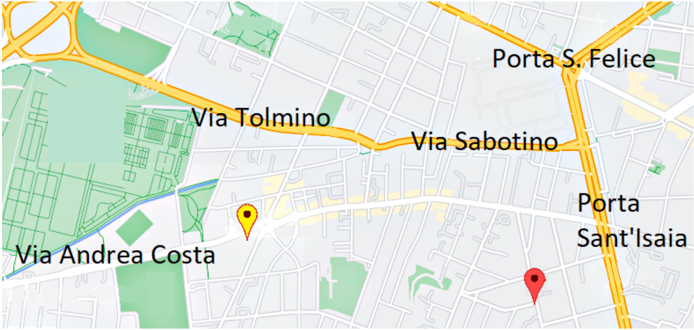
Traffic data -

- Peak hour (8:00 am - 9:00 am) generated during a football match on March 3rd 2010
- Daily flow one week before

Opearing scenario -

The reference initial position is located at the latitude $44°29'23.6''N$ and longitude $11°18'30.2''E$ coordinates. Within a local tangent plane East-North-Up reference frame, the AVs initial positions have been set as reported in Table with $v_x^i = 0$ and $v_y^i = 0, \forall i$. The aim consists in driving all the vehicles towards the parking area located close to the target position in the south-east side.

AV^1	AV^2	AV^3	AV^4	AV^5	AV^6	AV^7	AV^8	AV^9	AV^{10}	AV^{11}
70.0195	63.955	57.8905	51.826	45.7615	39.697	33.6325	27.54	21.503	15.44	9.374
386.4212	384.08	381.743	379.403	377.064	374.725	372.39	370.047	367.707	365.368	363.029



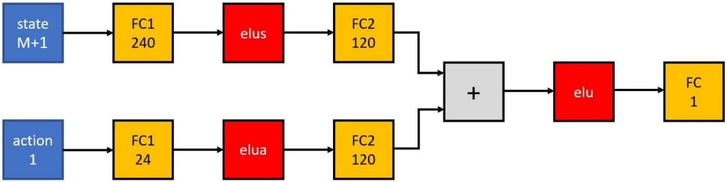
Simulations (4/12)

Simulation knobs -

- Vision radius: $R = 5\,[m]$,
- Curvature radius: $R^c_{min} = 2\,[m]$,
- Cost-to-go function weights: $R^i_x = I_{n_i},\; R^i_u = I_{m_i},\; i = 1, \ldots, L$
- Decision zone: $3.5\,[m]$ before each junction

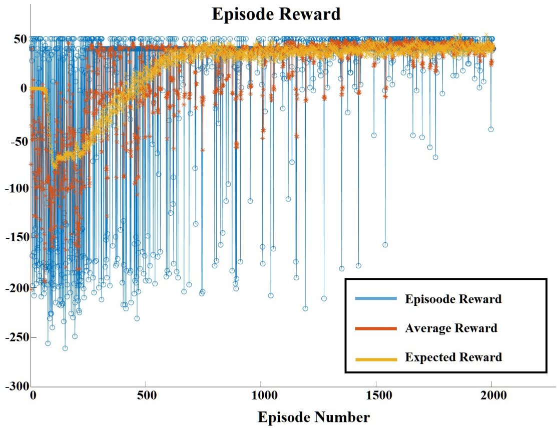
Neural network architecture -

The state input layer dimension is twice the number of edges of the considered URN: $2M = 358$



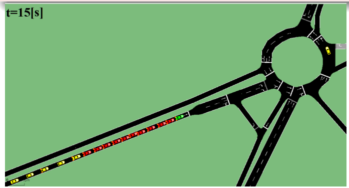
Neural network training -

- SUMO data set
- MATLAB Reinforcement Learning Toolbox built-in routines
- 2000 traffic episodes: each one defined as a finite sequence of time instants starting from the initial positions until the target x_f (parking area)

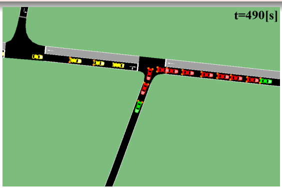


Splitting mode (1/3) -

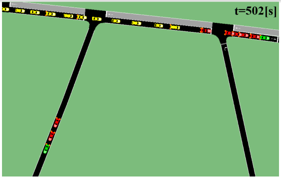
- traffic data in the time interval $8:00am - 8:30am$
- initially the platoon configuration is kept constant
- at $t = 482\,[s]$, the greedy actions $a^i(482) \neq a^1(482),\ i = 9, 10, 11,$ suggest to $AV^i, i = 9, 10, 11,$ to turn on the right while the others continue on the straight line
- two platoons $LF^1 = \{AV^1, \cdots, AV^8\}$ and $LF^2 = \{AV^9, AV^{10}, AV^{11}\}$ arise



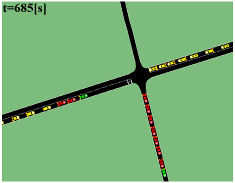
(a)



(b)



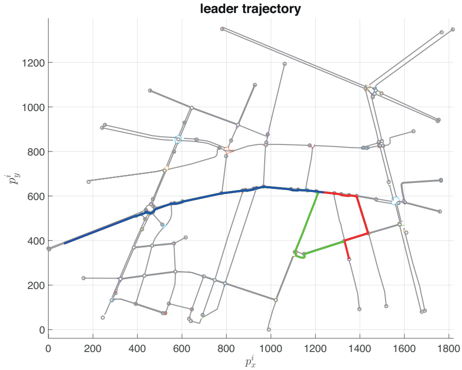
(c)

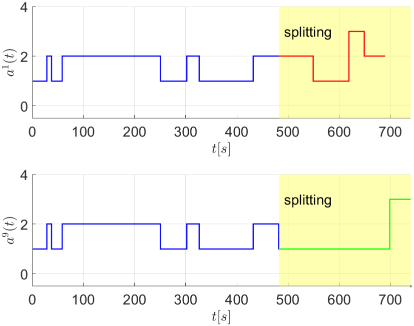


(d)

Splitting mode (2/3) -

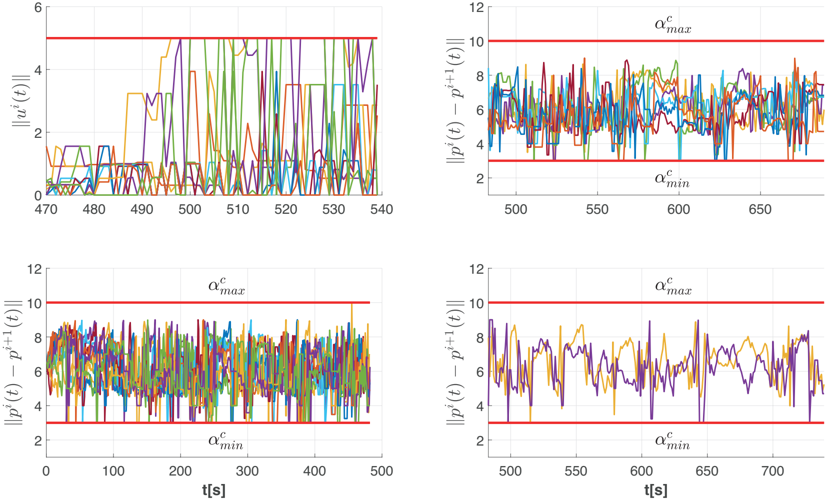
Routing actions behavior: the leader routing decision (green line) differs from AV^9 (red line)





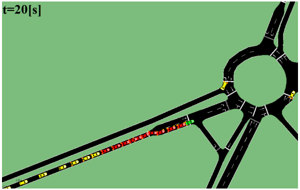
Splitting mode (3/3) -

Saturation constraints fulfillment

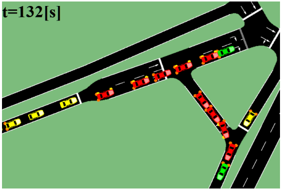


Queuing mode (1/3) -

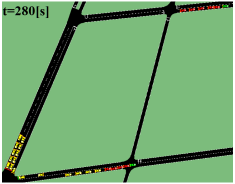
- traffic data in the time interval $8:30am - 9:00am$
- at $t \approx 123\,[s]$ the vehicles AV^i, $i = 6, \ldots, 11$, make different routing decisions with respect to the leader AV^1 and two new platoons arise
- at $t \approx 350[s]$ LF^2 queues to LF^1
- the platoon reaches the target at $t \approx 715\,[s]$



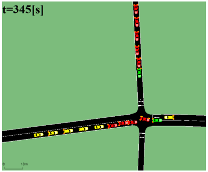
(e)



(f)



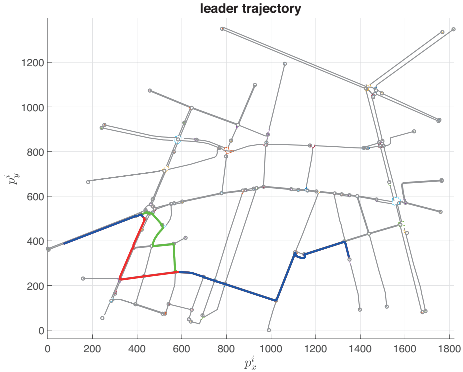
(g)

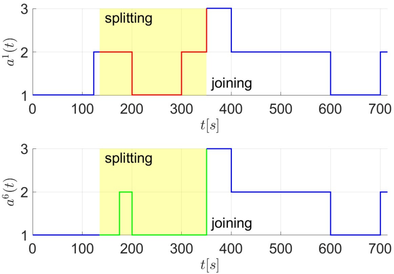


(h)

Queuing mode (2/3) -

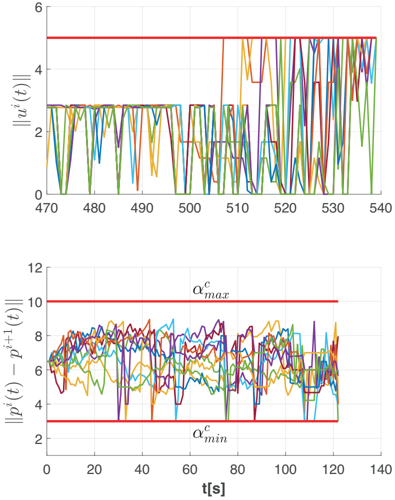
Routing actions behavior: the leader routing decision (green line) differs from AV^6 (red line)

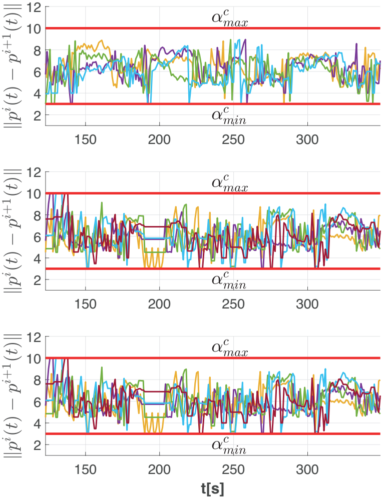




Queuing mode (3/3) -

Saturation constraints fulfillment





Comparisons -

- Contrast the proposed distributed Q-learning scheme with the Dijkstra algorithm
- Three operating scenarios:
  1. splitting mode
  2. queuing mode
  3. within the time window $8:00am - 8:30am$, the initial platoon configuration is initialized by imposing that all the vehicles have zero velocities, the leader is located at $(x_1^1(0), x_2^1(0)) = (874.54, 979.20)[m]$ and the target is $x_f = [1611.76, 883.38, 0, 0]^T\ [m]$

Simulation	Route percentage	**DRL-MPC**	**Dijkstra**
scenario 1	20% of route length	200 [s]	210 [s]
	50% of route length	400 [s]	500 [s]
	100% of route length	760 [s]	850 [s]
scenario 2	20% of route length	180 [s]	170 [s]
	50% of route length	400 [s]	450 [s]
	100% of route length	745 [s]	800 [s]
scenario 3	20% of route length	124 [s]	120 [s]
	50% of route length	280 [s]	250 [s]
	100% of route length	610 [s]	655 [s]

Concluding remarks

Conclusions -

- The path planning problem for vehicle platoons subject to routing decisions and operating in urban road networks has been addressed
- A new control architecture based on the joint exploitation of distributed reinforcement learning and model predictive control properties has been developed by fully taking advantage of the routing decisions
- Time-varying topologies of the multi-vehicle system have been considered according to the minimization of traffic congestion criteria

Future directions -

- Extend the proposed approach to take care of obstacle avoidance requirements
- Customize the strategy to comply with roadways including more than one lane so that grid vehicle topologies can be used
- Improve the performance of the distributed reinforcement learning algorithm by accelerating the distributed learning phase to get faster vehicle planning decision responses

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