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Bio-inspired control by overlapping adaptive clusters: a vehicle platoon case study

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Abstract: Clustering vehicles in a platoon by exchanging information through communication networks leads to an improvement in their performance with a moderate cooperation effort. In particular, in this paper, a bio-inspired methodology for overlapping coalitions of vehicles is proposed, which optimizes communication and control performance. The results obtained using the proposed adaptive clusters method are compared with the ones obtained by a conventional coalitional control strategy, and the comparison illustrates the improved efficiency of the proposed method.

Keywords: Bio-inspired control, coalitional control, overlapping topology, vehicle platoon

1. INTRODUCTION

Cooperative autonomous vehicles use control solutions based on existing vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication to reduce fuel consumption, ensure people's safety by avoiding collisions, improve travel comfort, and reduce the occupied space on roads by maintaining a safety distance between vehicles (Badue et al., 2019). The performance of the overall system depends on issues as: the use of the communication network, the chosen topology, the node management, and the bandwidth length. The same holds for the lifetime of batteries feeding actuators and wireless communications devices (Maestre et al., 2014). One possibility to balance the communication effort is the use of clustering methods, which dynamically reorganise the communication topology to reduce communication costs and improve performance (Maglaras and Katsaros, 2016). Additional advantages are: *i*) bandwidth optimisation - more clusters can use the same communication frequency with respect to geographical constraints; *ii*) network topology stability - clusters are formed to ensure better communication and performance so, they can be used for a long time if no other changes appear; *iii*) reduction of delays - the communication inside clusters can be organised more efficiently; *iv*) scalability - the division of the system into small groups allows the use of distributed control strategies to optimise the performances of the whole group (Ayyub et al., 2022).

Based on these advantages, there are some studies in the literature focused on coalitional control. For example, (Leon Calvo and Mathar, 2018) use a coalitional approach to improve the traffic flow by grouping the vehicles in platoons. Another study based on the coalitional game theory is represented by (Youyun et al., 2019), where the performance of the network communication is improved to ensure the stability of the whole cluster. Moreover, (Barreiro-Gomez and Zhu, 2022) propose a solution where the Shapley values are used to determine the most relevant links to select the coalition. Finally, (Baldivieso-Monasterios and Trodden, 2021) propose a coalitional distributed model predictive control strategy for a coupled mass-spring-damper system where the coalitions are chosen to ensure feasible and stable control.

The idea of cooperative clusters comes from nature, where cooperative formations are naturally formed. Each formation has its own shape and motion, e.g., flocking motion for birds, schools of fish, and herds for animals. These examples from nature succeed to form and move in their groups using multiple communication types. Moreover, each member of the formation has to pay attention only to its neighbours in order not to collide (Lewis et al., 2014). Three rules which govern the motion of clusters have been determined in (Reynolds, 1987): *i)* avoid collision with neighbours; *ii)* match velocity and direction of motion with

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your neighbours; *iii)* stay close to your neighbours. The advantages of an adaptive cluster compared to a single agent are that the group can ensure robustness when an agent from the group fails, reconfigurability and target localisation. A cooperative cluster has four main properties: group objective, agents (members), information topology, and control algorithms. The group objectives may include flocking, escorting, vehicle formation maintenance, cooperative load transport, and optimal sensing (Bai et al., 2011). One of the most studied clustering methods for vehicles is vehicle platooning (Aghababa and Saif, 2020). Among the advantages of this approach, we can mention the increase of safety, the reduction of costs and pollution by decreasing the amount of used fuel (Fang et al., 2021).

This paper proposes a coalitional control strategy to maintain constant distances between the vehicles of a platoon. Each vehicle is controlled by an individual controller and can share and receive information (i.e., sensors measurements, internal states values) through dynamic communication links which can be enabled or disabled. The communication topology is chosen online to improve the performance of the platoon and to reduce the number of active communication links. To design the corresponding controllers for the vehicles, two solutions based on the minimisation of a cost function are studied and compared with a conventional coalitional control strategy based on linear matrix inequalities (LMIs). Inspired by groups from nature, the vehicles have to find the best way to cooperate to reach the imposed target with minimal costs.

The main novelty of the paper is the use of overlapping coalitions, which have not been used before in the context of coalitional control. In particular, overlapping coalitions allow a given vehicle (agent) to be member of multiple coalitions at the same time. The proposed methodology *fuzzifes* the discrete set of topologies to improve performance because there are more degrees of freedom to compute the controller, in comparison to conventional coalitional control design methods.

2. PROBLEM SETTING

Following the coalitional control framework of (Chanfreut et al., 2021), we consider a system formed by M subsystems, $\mathcal{S} = \{1, 2, .., M\}$, each of them with dynamics:

$$\begin{cases} x_i(k+1) = A_{ii}x_i(k) + B_{ii}u_i(k) + d_i, \\ d_i = \sum_{j \in S-\{i\}} A_{ij}x_j(k) + B_{ij}u_j(k), \end{cases} \quad (1)$$

where $x_i \in \mathbb{R}^n$ and $u_i \in \mathbb{R}^m$ represent the state and the input of subsystem $i \in \mathcal{S}$, respectively, and d_i represents the disturbance that affects subsystem i.

Starting from (1), the equation that describes the dynamics of the overall system is given by:

$$x_{\mathcal{S}}(k+1) = A_{\mathcal{S}}x_{\mathcal{S}}(k) + B_{\mathcal{S}}u_{\mathcal{S}}(k), \quad (2)$$

where $x_{\mathcal{S}} \in \mathbb{R}^{n_{\mathcal{S}}}$ and $u_{\mathcal{S}} \in \mathbb{R}^{m_{\mathcal{S}}}$ aggregate all states and inputs of all sub-systems $i \in \mathcal{S}$.

The communication network between subsystems is described by a graph $(\mathcal{S}, \mathcal{L})$, where $\mathcal{S}$ is the set of subsystems and $\mathcal{L}$ is the set of edges representing communication directed links between agents:

$$\begin{cases} L \subseteq L^S = \{\{i,j\} | \{i,j\} \subseteq S, i \neq j\}, \\ T = \{\Lambda | \Lambda \subseteq L\}. \end{cases} \quad (3)$$

The directed links between agents can be enabled or disabled by the controller and we define the network topology $\Lambda \in T$ as the set of active links at a given time. Also, coalitions are defined as the partitions of the set of agents due to the network configuration. Since the partitions are not disjoint (i.e., with overlapping clusters, a given agent can belong to more than one coalition). To clarify this, let us focus on the overall feedback gain, which defines the control law of the overall system:

$$u_{\mathcal{S}}(k+1) = K^{\Lambda}x_{\mathcal{S}}(k), \quad (4)$$

where K^{Λ} is the overall feedback gain control matrix, corresponding to topology $\Lambda \in T$. In particular, the objective is to steer the state of the overall system (2) to the origin by minimizing a global cost function:

$$\begin{aligned} J(u_{\mathcal{S}}, \Lambda, k) = \sum_{j=0}^{\infty} \Big[& x_{\mathcal{S}}^T(k+j)Q_{\mathcal{S}}x_{\mathcal{S}}(k+j) + \\ & + u_{\mathcal{S}}^T(k+j)R_{\mathcal{S}}u_{\mathcal{S}}(k+j) + c\xi(\Lambda(k+j)) \Big], \end{aligned} \quad (5)$$

where $Q_{\mathcal{S}} \in \mathbb{R}^{n_{\mathcal{S}} \times n_{\mathcal{S}}}$ and $R_{\mathcal{S}} \in \mathbb{R}^{m_{\mathcal{S}} \times m_{\mathcal{S}}}$ are positive defined weighing matrices, $c \in \mathbb{R}$ is the weight of the communication links enabled in topology Λ, and $\xi(\Lambda)$ is the communication cost of topology Λ, which is defined as:

$$\xi(\Lambda) = (no^*(K^{\Lambda})/n - M)/2, \quad (6)$$

where $no^*(K^{\Lambda})$ represents the number of the non-zero elements of the control matrix K^{Λ}, n is the number of the states of each subsystem.

Since the minimization of global cost function (5) is difficult in real-time, the infinity sum is replaced by the following finite sum:

$$\begin{aligned} J(\Lambda) = \sum_{j=0}^{N} \Big[& x_{\mathcal{S}}^T(k+j)Q_{\mathcal{S}}x_{\mathcal{S}}(k+j) + \\ & + u_{\mathcal{S}}^T(k+j)R_{\mathcal{S}}u_{\mathcal{S}}(k+j) \Big] + cN\xi(\Lambda(k)), \end{aligned} \quad (7)$$

where $N \in \mathbb{Z}_+$ represents the number of time samples for which system $\mathcal{S}$ is evaluated. This cost function depends only on the topology $\Lambda \in T$ because the command $u_{\mathcal{S}}$ is computed using (4) and the parameters of K^{Λ} are determined in advance.

To determine the topology for the next N time instants, the cost function (7) is minimised using $\Lambda \in T$. Finally, the whole control method is described in Algorithm 1.

Algorithm 1: Control method

if *mod(k, N)!=0* **then**
  Compute and apply the command using (4);
else
  (1) All subsystems share their current states;
  (2) Starting from the current values of the state of the overall system $x_{\mathcal{S}}(k)$:
    (a) For all $\Lambda \in T$, compute the cost function $J(\Lambda)$ using (7) and model (2);
    (b) The smallest value for $J(\Lambda)$ determines the topology Λ, which is used by the system for the next N time samples.
end

Remark 1. All the links are considered enabled when the system has to switch the communication topology, so that all subsystems can share their inputs and states.

3. ANALYSIS OF LINKS RELEVANCE USING GAME THEORY

Game theory can be used to find out which links are more relevant. This can be done using a characteristic function, $f(\Lambda)$, which determines the benefits obtained using a certain coalition Λ. For this reason, the characteristic function is computed using the cost defined by (7), i.e., $f(\Lambda) = J(\Lambda)$ (Maestre et al., 2014). In order to have a link game where the communication links represent the players, the $f(\Lambda_0)$, with $\Lambda_0 = \{\emptyset\}$ (i.e., the subsystems do not communicate) has to be 0. To fulfil it, the characteristic function is redefined as:

$$f(\Lambda) = f(\Lambda) - f(\Lambda_0). \tag{8}$$

The characteristic function evaluates the topologies, but the Shapley value must be used to obtain an evaluation of each link $l \in \Lambda$:

$$\sigma_l(\Lambda, u) = \sum_{\Omega \subseteq \Lambda - \{l\}} \frac{\xi(\Omega)!(\xi(\Lambda) - \xi(\Omega) - 1)!}{\xi(\Lambda)!} \tilde{\sigma} \tag{9}$$

$$\tilde{\sigma}(\Omega) = w(\Omega \cup \{l\}) - w(\Omega), \tag{10}$$

where

$$w(\Omega) = \sum_{j=0}^{N} [x_{\mathcal{S}}^T(k+j) Q_{\mathcal{S}} x_{\mathcal{S}}(k+j) + \\ + u_{\mathcal{S}}^T(k+j) R_{\mathcal{S}} u_{\mathcal{S}}(k+j)]. \tag{11}$$

The Shapley value efficiently distributes the communication and performance costs between links for a given state x_S and can be used to determine the most relevant links.

4. FEEDBACK DESIGN METHODS

In this section, some design alternatives to compute the control feedback gains K^Λ are assessed. All methods begin with the gain matrix from the decentralized case and finish with the last one, which is the centralized case. Each algorithm has as an input variable a large set of initial states for the overall system (denoted S_0) to remove the bias caused by a specific system configuration. The expected output of each algorithm is the control feedback gain matrix for each communication topology.

4.1 LMI-based methodology

The first method used is based on a LMI-based optimisation problem, in which the control gain matrix is determined for each topology, solving a set of linear inequalities. The advantage of this method is that it requires low computational power to compute these matrices. For more details regarding this method, the interested readers are referred to (Chanfreut et al., 2021).

4.2 Independent state-feedback gain matrix for each communication topology (IK)

The second method was first introduced by (Maxim et al., 2022) and, for each topology, the feedback matrix K^Λ is determined by minimising a cost function, which is one step in Algorithm 2. The advantage of this approach is that it can be used to compute the control gain matrix for overlapping topologies. The platoon has more degrees of freedom to choose the best topology to improve its performance.

Algorithm 2: IK

Starting from a large set of initial states S_0 of the overall system $x_S(k)$, for each initial state $x_S(k)$ do the following:
for *all* $\Lambda \in T$ **do**
  Find the feedback matrix K^Λ minimising the cost function:
  $J(K^\Lambda) = \sum_{j=0}^{k_{stop}} [x_{\mathcal{S}}^T(k+j) Q_{\mathcal{S}} x_{\mathcal{S}}(k+j) + u_{\mathcal{S}}^T(k+j) R_{\mathcal{S}} u_{\mathcal{S}}(k+j)]$;
  The state $x_{\mathcal{S}}(k+j)$ is obtained using (2), $j \geq 1$;
  The command $u_{\mathcal{S}}^T(k+j)$ is computed using (4).
end

4.3 Modular K matrix suitable for all possible communication topologies (ModK)

This subsection presents a method that has as result a modular matrix K, from which the state feedback gain matrix for each topology can be extracted. The method reduces the required computational power. Thus, the components of this matrix K are determined in an incremental approach for each topology, considering also the feedback gain matrix obtained for previous topologies, based on Algorithm 3.

Algorithm 3: ModK

Starting from a large set of initial states S_0 of the overall system $x_S(k)$, for each initial state $x_S(k)$ do the following:
  Find the matrix K such that;
for *all* $\Lambda \in T$ **do**
  Defining matrix K^Λ considering the common elements from matrix K, which have been already computed in the previous steps;
  Find the unknown elements of feedback matrix K^Λ (which are specific for topology Λ) by minimising the cost function:
  $J(K^\Lambda) = \sum_{j=0}^{k_{stop}} [x_{\mathcal{S}}^T(k+j) Q_{\mathcal{S}} x_{\mathcal{S}}(k+j) + u_{\mathcal{S}}^T(k+j) R_{\mathcal{S}} u_{\mathcal{S}}(k+j)]$;
  Add in matrix K the new elements corresponding to the matrix K^Λ;
  $x_{\mathcal{S}}(k+j)$ is obtained using (2), $j \geq 1$;
  The command $u_{\mathcal{S}}^T(k+j)$ is computed using (4).
end

The methods represented by Algorithms 2 and 3 begin to compute the feedback gain matrix starting from the decentralised coalition and increase the complexity of the coalitions until the centralised coalition when all links are enabled. Again, this method gives the possibility for a platoon to have more degrees of freedom to choose the best topology by using overlapping topologies. The methods described in this section are used to design the feedback gain matrix of each communication topology for a vehicle platoon in a case study that will be described in the next section.

5. CASE STUDY AND RESULTS

This section illustrates the equations that describe the longitudinal dynamics of a vehicle platoon (see Fig. 1) and the results obtained using the proposed coalitional control strategy.

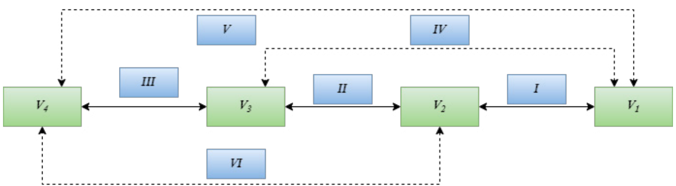

Fig. 1. Vehicle platoon

The paper considers a platoon that is formed by a leader and four followers. The leader vehicle, which is denoted by V_0 (and does not appear in Fig. 1), is considered moving with a constant velocity (i.e., its acceleration is null). Thus, the proposed control strategies will be used only for the follower vehicles, denoted in Fig. 1 with V_i, $i = \{1, 2, 3, 4\}$. Model (12), from the work by (Chanfreut et al., 2020), illustrates the dynamics of a follower vehicle:

$$\begin{bmatrix} \dot{e}_{d_i}(t) \\ \ddot{e}_{v_i}(t) \\ \ddot{a}_i(t) \\ \ddot{a}_{i-1}(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 & -t_k & 0 \\ 0 & 0 & -1 & 1 \\ 0 & 0 & -1/\tau & 0 \\ 0 & 0 & 0 & -1/\tau \end{bmatrix} \begin{bmatrix} e_{d_i}(t) \\ e_{v_i}(t) \\ a_i(t) \\ a_{i-1}(t) \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1/\tau & 0 \\ 0 & 1/\tau \end{bmatrix} \begin{bmatrix} u_i(t) \\ u_{i-1}(t) \end{bmatrix}, \quad (12)$$

where $e_{d_i}(t)$ is the error between the distance d_i maintained by vehicle i to vehicle $i-1$ and the target distance, defined as $d_{ri} = d_0 + t_k v_i(t)$, d_0 representing the safety distance, $e_{v_i}(t)$ represents the error between the velocities of vehicles $i-1$ and i, $t_k = 0.7s$ is the time headway, and $\tau = 0.1s$ is the time constant.

The parameters used for computing the cost function (7) are $Q_S = 0.1I_n$, $R_S = 0.1I_n$, the link weight is set as $c = 0.002$, $N = 10$ time samples, $k_{stop} = 90$ time samples, and the sampling period is $T_s = 0.1s$. The large set of initial states S_0 used by Algorithms 2 and 3 represents 1000 random values between $-6m \leq e_{d_i}(k) \leq 6m$, $-4m/s \leq e_{v_i}(k) \leq 4m/s$, $-10m/s^2 \leq a_i(k) \leq 10m/s^2$.

The communication network is formed by six links, $L = \{I, II, III, IV, V, VI\}$, as depicted in Fig. 1, which allow bidirectional communication between all vehicles. One of the novelties of this paper is the introduction of overlapping topologies, which allow better optimisation of network communication. For example, if the links I and II are active, then the formed topology includes the vehicles $\{V_1, V_2, V_3\}$ and the communication between these vehicles is provided by links I, II and IV. If, at some point, there exists a low coupling between vehicles V_1 and V_3, then these two vehicles do not need to exchange data, i.e., the communication link IV is disabled. An overlapping topology will allow only communication between vehicle V_1 and V_2 (link I is enabled) and between V_2 and V_3 (link II is enabled), resulting the following overlapping topology, $\{\{V_1, V_2\}, \{V_2, V_3\}\}$, in which V_2 is the common vehicle. The possible topologies for a platoon formed by four vehicles are presented in table 1.

Remark 2. Note that links I, II and III are used to design the coalitions, whereas links IV, V and VI are only used to ensure direct communication between their corresponding vehicles. For this reason, links IV, V and VI cannot be used to form a coalition (e.g., the coalition between the vehicles V_1 and V_3, via link IV, is not allowed).

In order to illustrate the difference between overlapping typologies and the method used to compute the feedback matrix, an example is used: let us consider the topologies $\Lambda_1 = \{V_1, V_2\}$, $\Lambda_9 = \{V_2, V_3\}$, $\Lambda_6 = \{V_1, V_2, V_3\}$ and $\Lambda_2 = \{\{V_1, V_2\}, \{V_2, V_3\}\}$. The methods based on LMI and IK return a feedback gain matrix for each topology, except for Λ_2, which is an overlapping topology and only IK can determine a control matrix for it: $K^{\Lambda_1} = \begin{bmatrix} K_{11}^{\Lambda_1} & K_{12}^{\Lambda_1} & 0 & 0 \\ K_{21}^{\Lambda_1} & K_{22}^{\Lambda_1} & 0 & 0 \\ 0 & 0 & K_{33}^{\Lambda_1} & 0 \\ 0 & 0 & 0 & K_{44}^{\Lambda_1} \end{bmatrix}$, $K^{\Lambda_9} = \begin{bmatrix} K_{11}^{\Lambda_9} & 0 & 0 & 0 \\ 0 & K_{22}^{\Lambda_9} & K_{23}^{\Lambda_9} & 0 \\ 0 & K_{32}^{\Lambda_9} & K_{33}^{\Lambda_9} & 0 \\ 0 & 0 & 0 & K_{44}^{\Lambda_9} \end{bmatrix}$, $K^{\Lambda_6} = \begin{bmatrix} K_{11}^{\Lambda_6} & K_{12}^{\Lambda_6} & K_{13}^{\Lambda_6} & 0 \\ K_{21}^{\Lambda_6} & K_{22}^{\Lambda_6} & K_{23}^{\Lambda_6} & 0 \\ K_{31}^{\Lambda_6} & K_{32}^{\Lambda_6} & K_{33}^{\Lambda_6} & 0 \\ 0 & 0 & 0 & K_{44}^{\Lambda_6} \end{bmatrix}$,

$K^{\Lambda_2} = \begin{bmatrix} K_{11}^{\Lambda_2} & K_{12}^{\Lambda_2} & 0 & 0 \\ K_{21}^{\Lambda_2} & K_{22}^{\Lambda_2} & K_{23}^{\Lambda_2} & 0 \\ 0 & K_{32}^{\Lambda_2} & K_{33}^{\Lambda_2} & 0 \\ 0 & 0 & 0 & K_{44}^{\Lambda_2} \end{bmatrix}$, where $K_{ij}^{\Lambda_z} \in \mathbb{R}^{1 \times n}$.

For each coalition, these two methods compute a new control matrix compared to the method $ModK$, which computes a single matrix for all topologies and from it all feedback gain matrices are extracted for each topology, including the overlapping topologies: $K^{\Lambda_1} = \begin{bmatrix} K_{11} & K_{12} & 0 & 0 \\ K_{21} & K_{22} & 0 & 0 \\ 0 & 0 & K_{33} & 0 \\ 0 & 0 & 0 & K_{44} \end{bmatrix}$, $K^{\Lambda_9} = \begin{bmatrix} K_{11} & 0 & 0 & 0 \\ 0 & K_{22} & K_{23} & 0 \\ 0 & K_{32} & K_{33} & 0 \\ 0 & 0 & 0 & K_{44} \end{bmatrix}$, $K^{\Lambda_6} = \begin{bmatrix} K_{11} & K_{12} & K_{13} & 0 \\ K_{21} & K_{22} & K_{23} & 0 \\ K_{31} & K_{32} & K_{33} & 0 \\ 0 & 0 & 0 & K_{44} \end{bmatrix}$, $K^{\Lambda_2} = \begin{bmatrix} K_{11} & K_{12} & 0 & 0 \\ K_{21} & K_{22} & K_{23} & 0 \\ 0 & K_{32} & K_{33} & 0 \\ 0 & 0 & 0 & K_{44} \end{bmatrix}$, where $K_{ij} \in \mathbb{R}^{1 \times n}$.

The communication cost also represents a difference between the overlapping coalitions and the classical coalitional method. For example, the coalitions $\Lambda_2 = \{\{V_1, V_2\}, \{V_2, V_3\}\}$ and $\Lambda_6 = \{V_1, V_2, V_3\}$ use the same links $\{I, II\}$, but the communication cost is different because in coalition Λ_2 vehicles V_1 and V_3 do not communicate (i.e., link IV is disabled), compared to coalition Λ_6, in which link IV is enabled. Table 1 illustrates all communication links and costs required by each coalition.

This work proposes two new methods, IK and $ModK$, to compute the controllers for vehicles, i.e., the feedback gain matrix. The results were compared with the conventional coalitional control based on the LMI approach. The

Table 1. Communication topologies of a vehicle platoon formed by four vehicles

T	Links	$\xi(\Lambda)$	Vehicles	T	Links	$\xi(\Lambda)$	Vehicles
Λ_0	$\{\emptyset\}$	0	$\{V_1\}$, $\{V_2\}$, $\{V_3\}$, $\{V_4\}$	Λ_7	$\{I, III\}$	2	$\{V_1, V_2\}$, $\{V_3, V_4\}$
Λ_1	$\{I\}$	1	$\{V_1, V_2\}$	Λ_8	$\{I, II, III, VI\}$	4	$\{V_1, V_2\}$, $\{V_2, V_3, V_4\}$
Λ_2	$\{I, II\}$	2	$\{V_1, V_2\}$, $\{V_2, V_3\}$	Λ_9	$\{II\}$	1	$\{V_2, V_3\}$
Λ_3	$\{I, II, III\}$	3	$\{V_1, V_2\}$, $\{V_2, V_3\}$, $\{V_3, V_4\}$	Λ_{10}	$\{II, III\}$	2	$\{V_2, V_3\}$, $\{V_3, V_4\}$
Λ_4	$\{III\}$	1	$\{V_3, V_4\}$	Λ_{11}	$\{I, II, III, IV\}$	4	$\{V_3, V_4\}$, $\{V_1, V_2, V_3\}$
Λ_5	$\{I, II, III, IV, VI\}$	5	$\{V_1, V_2, V_3\}$, $\{V_2, V_3, V_4\}$	Λ_{12}	$\{II, III, VI\}$	3	$\{V_2, V_3, V_4\}$
Λ_6	$\{I, II, IV\}$	3	$\{V_1, V_2, V_3\}$	Λ_{13}	$\{I, II, III, IV, V, VI\}$	6	$\{V_1, V_2, V_3, V_4\}$

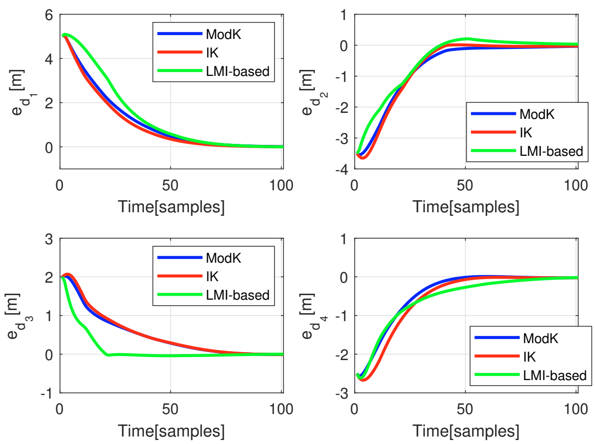

Fig. 2. Distance error between vehicles

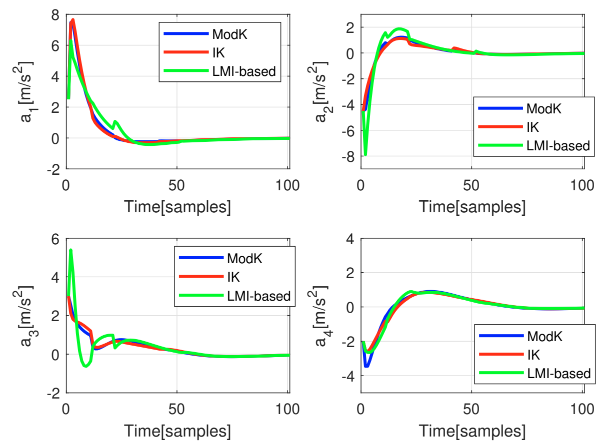

Fig. 4. Acceleration of vehicles

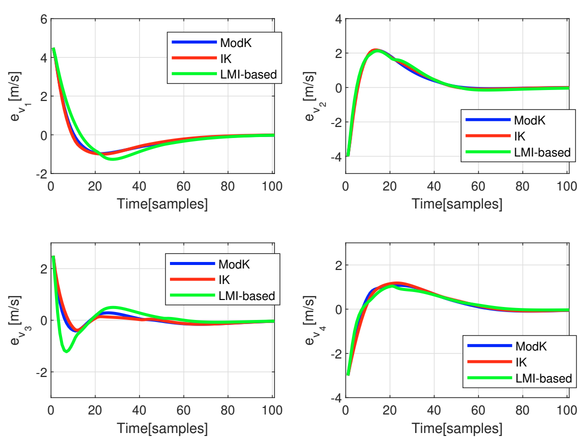

Fig. 3. Velocity error between vehicles

methods IK and $ModK$ are allowed to use all possible topologies from table 1, but the one based on LMI uses only the classical topologies (i.e., Λ_0, Λ_1, Λ_4, Λ_6, Λ_7, Λ_9, Λ_{12}, Λ_{13}).

In Figs. 2-4, the distance errors between vehicles, velocity errors and accelerations of vehicles are illustrated. From these figures, it results that the states of each vehicle are led to the origin, meaning that the vehicles maintain a desired distance to the vehicle in front. Moreover, using IK and $ModK$ methods, the acceleration of the vehicles has smaller variations compared to the results obtained by the LMI approach. This can be seen also in Figs. 2-3, where the distance and velocity errors are decreasing smoother to zero compared to the case of LMI. A sudden variation of the acceleration leads to decreased passengers' comfort and an increase of fuel consumption and emissions. Every $N = 10$ samples, the platoon, using Algorithm 1 described in Section 3, decides which is the new topology that offers better control performances and reduced fuel cost and communication. The communication topologies and the time when these were used are illustrated in Fig. 5. Using the LMI based method, the first topology chosen is Λ_4. This one assumes that vehicles $\{V_3, V_4\}$ have communications links active and exchange information between them. The next two topologies are Λ_9 and Λ_1. This means that only vehicles V_2 and V_3 and respectively vehicles V_1 and V_2 exchange data between them, while the remaining platoon uses a decentralised controller based only on the information from the local sensors. In the time sample interval $[40, 50]$, the links I and III are active, allowing communication between vehicles $\{V_1, V_2\}$ and $\{V_3, V_4\}$, i.e., Λ_7. The last link active is II, which assumes a communication between vehicles $\{V_2, V_3\}$, while the remaining platoon uses a decentralised controller. The second method, IK, initially uses the overlapping topology Λ_{11}, in which the links $\{I, II, III, IV\}$ allow communication between vehicles $\{V_3, V_4\}$ and between $\{V_1, V_2, V_3\}$. The topology Λ_1 is used during the sample interval $[20, 30]$ and only the communication between vehicles V_1 and V_2 is active. In the interval $[30, 60]$, the overlapping topology Λ_2 activates the links $\{I, II\}$ so that V_1 communicates with V_2, and V_2 with V_3. The rest of the vehicles use a decentralised control solution based on sensors measurements. The last method is the one that obtain the largest reduction of communication costs between vehicles. The method uses only the typologies Λ_3 and Λ_1. Topology Λ_3 is an overlapping topology in which the communication links are active only for the groups $\{V_1, V_2\}$, $\{V_2, V_3\}$ and, respectively, the group $\{V_3, V_4\}$.

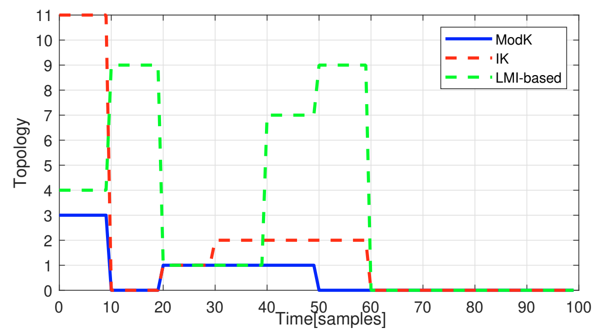

Fig. 5. Network mode

Topology Λ_1 assumes that only the vehicles $\{V_1, V_2\}$ are linked. From Figs. 2-5 it can be observed that the decentralised solution, Λ_0, is used in all three cases when the states are close to the origin. Also, from these figures, it can be observed that for the methods IK and $ModK$ all the states reach first the origin; from that point on, the communication links are disabled and, the platoon uses only the decentralised control, i.e., topology Λ_0. The maximum values of cost functions of the three methods are: $J_{ModK} = 177.6$, $J_{IK} = 172.9$, $J_{LMI} = 203.4$, where the cost J is computed for all simulation time i.e., 100 time samples, and is the same cost as the one used by Algorithms 2 and 3. It can be noticed that methods which use overlapping coalitions, have similar results and outperform the method based on LMI.

The Shapley (9) and characteristic function (8) values of the communication network links, (only I, II and III), are illustrated in table 2. The link with the smallest values is I, which connects vehicles $\{V_1, V_2\}$. Moreover, this result is in accordance with the characteristic values, which have smaller values compared to all topologies with a single link. These values prove that the communication between vehicles V_1 and V_2 has the greatest relevance in the performance of the overall platoon.

Table 2. Characteristic function and Shapely values

Links	I		II		III	
Method	f	σ_l	f	σ_l	f	σ_l
$ModK$	-19.64	-4.49	2.68	0.51	-2.16	-0.14
IK	-19.29	-5.41	11.05	2.12	-1.4	-0.98
LMI	-21.98	-6.47	14.92	2.27	-4.9	-1.82

6. CONCLUSIONS

The paper proposes a bio-inspired coalitional control strategy to regulate distances between the vehicles of a platoon. The novelties of the paper are represented by the use of two new methods based on the minimisation of a cost function for designing the controllers for each topology and the introduction of overlapping topologies, which can better optimise the use of the communication network. The results were compared with a solution based on the LMI approach. The simulations show that the proposed methods with overlapping coalitions outperform the LMI-based classical coalition control approach.

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