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Review article

A survey on clustering methods for distributed and networked control systems

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ABSTRACT

Clustering strategies are becoming increasingly relevant to boost the scalability of distributed control methods by focusing the cooperation efforts on highly coupled agents. They are also relevant in systems where failing communication links and plug-and-play events are considered, which demand increased flexibility and modularity. This article reviews commonalities and differences of those distributed strategies that exploit the degree of interaction between control agents to boost the mentioned properties, frequently leading to control structures where the communication network becomes a decision variable that may evolve dynamically. Taxonomies based on the control law employed, the criterion for selecting the network topology, its static/dynamical nature, the control architecture, and the provided theoretical properties, are given. Additionally, a review of applications in power networks, water systems, vehicle and traffic systems, renewable energy plants, and chemical processes is provided.

1. Introduction

The sheer size and possible geographical dispersion of large-scale systems (Kordestani, Safavi, & Saif, 2021; Scattolini, 2009), such as smart grids (Qi, Liu, & Christofides, 2011), water networks (Negenborn, van Overloop, Keviczky, & De Schutter, 2009), traffic systems (Hernández, Ossowski, & Garcıa-Serrano, 2002), and intelligent buildings (Scherer, Pasamontes, Guzmán, Álvarez, Camponogara, & Normey-Rico, 2014), causes the implementation of centralized strategies to demand strong computational and communication resources. In contrast to the centralized approach, where a single controller has full decision-making power and complete knowledge of the system, distributed strategies rely on a decentralization of the overall problem where, typically, a set of local controllers, also referred to as *agents*, manage the different systems partitions or *subsystems* (Hernández et al., 2002; Negenborn et al., 2009; Qi et al., 2011; Scherer et al., 2014), thus providing the overall control architecture higher scalability and redundancy at the expense of a more sophisticated design.

In this setting, global performance is highly influenced by the extent to which communication and coordination among agents is considered (Rawlings & Stewart, 2008; Zheng, Li, Li, & Ren, 2017). It is well-known that fully coordinated systems can attain optimality, while the complete absence of inter-agent communication may lead to undesirable performance losses, which augment with the degree of subsystems' interactions (Venkat, Rawlings, & Wright, 2004). However, coordination demands increased communication and algorithm complexity, and the need to deal with additional constraints, e.g., due to the connectivity and capacity of the network and the timing requirements for real-time operation. In particular, the information exchange in distributed control can range from tens of bytes to megabytes per time step, depending on the control problem and the algorithm employed (Maestre, et al., 2015), and increases with the number of controllers involved in the negotiation.

Recently, a number of research works have explored distributed structures that seek a balance between the system performance and the coordination efforts, which can be measured by, e.g., the communication and computational demands (Dörfler, Jovanović, Chertkov, & Bullo, 2014; Pajic, Sundaram, Pappas, & Mangharam, 2011; Sadi & Ergen, 2017; Schuler, Münz, & Allgöwer, 2014; Wei, Li & Zheng, 2020; Yang, Zhang, Zheng, & Qian, 2020). This two-fold goal has led to control structures with *partial*, and occasionally dynamic, subsystems communication, avoiding the need for full information sharing. From a static viewpoint, the problem is similar to that of *system partitioning*, which searches for suitable decompositions of the global system into subsystems and assigns variables to different control agents (Motee & Sayyar-Rodsari, 2003; Ocampo-Martinez, Bovo, & Puig, 2011). In this way, agents can be (re)arranged into *operational units* or *clusters* that determine their actions using intra-area information, i.e., without communication with agents outside the cluster (Fele, Maestre, & Camacho, 2017; Ocampo-Martinez et al., 2011; Zheng, Wei, & Li, 2018).

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The problem of *clustering* is closely related to the machine learning framework (Xu & Wunsch, 2008), where large volumes of data need to be classified into subsets based on properties of interest. In the context of multi-agent systems, the goal is to find sets of strongly coupled variables and highly interacting agents so as to reduce the cooperation effort with minimal impact on the overall performance. A representative application is power systems, where the huge amount of information and control inputs to be managed motivates the system decomposition into operational areas (Chakrabortty, 2012; Cotilla-Sanchez, Hines, Barrows, Blumsack, & Patel, 2013; Nayeripour, Fallahzadeh-Abarghouei, Waffenschmidt, & Hasanvand, 2016; Zhong, Nobile, Bose, & Bhattacharya, 2004). Other works consider *sparsity-promoting* penalties and constraints in the controller design so as to detect and eliminate communication links not leading to significant performance improvements, e.g., Babazadeh and Nobakhti (2016), Dörfler et al. (2014), Guicherd, Trodden, Mills, and Kadirkamanathan (2020), Jovanović and Dhingra (2016), Lin, Fardad, and Jovanović (2013). The latter also allows to optimize the use of communication resources and results in a distributed architecture where the feedback received by the set of networked agents is limited and may vary in time. In this regard, both clustering-based and sparsity-promoting approaches have been implemented in a static and dynamic manner, being the latter the main research area of interest in this work. The extra flexibility of dynamic schemes allows adapting the controller structure to the system needs while bringing new challenges, e.g., deciding which variables need to be shared and among which agents; dealing with restricted and varying neighboring information; and studying properties such as overall system and partition stability in such setting.

Furthermore, distributed control systems may suffer unpredicted malfunctions, such as communication links failures and communication time delays, which lead to intermittent communication and loss of information. Control structures able to handle switching communication topologies are of special interest for systems operating in presence of the mentioned network faults, and applications of a switching communication nature, e.g., di Bernardo, Falcone, Salvi, and Santini (2015) and Li, Bian, Li, Xu, and Wang (2020) consider vehicle systems where the vehicle-to-vehicle links form and break due to cars joining or leaving the system and to communication failures; Schiffer, Dörfler, and Fridman (2017) provides robust stability guarantees in a power network system that may suffer from links failures and packet losses; and Riverso, Boem, Ferrari-Trecate, and Parisini (2016) proposes a *plug-and-play* architecture able to detect and isolate faulty subsystems not to compromise overall stability and constraints satisfaction.

Motivated by the increasing amount of works in the control literature where the degree of interaction between control entities is exploited to increase the scalability and flexibility of the approach, this article offers a survey where the most relevant commonalities and differences are exposed. In particular, we focus on works that seek to:

(i) Provide a trade-off between system performance and communication/coordination burden as a way to increase the controller efficiency and scalability, e.g., Dörfler et al. (2014), Fele et al. (2017), Lian, Chakrabortty, and Duel-Hallen (2017).
(ii) Deal with communication constraints such as inter-agents links failures or the requirement of a minimum distance to enable effective communication, e.g., Lu, Yu, Lai, Guerrero, and Zhou (2016), Scherer et al. (2014), Smith and Bullo (2009).
(iii) Deal with structural changes of the system such as joining/leaving subsystems, e.g., Li et al. (2020), Riverso, Farina, and Ferrari-Trecate (2014).

As will be seen, the first goal frequently leads to clustering methods where the communication, and hence coordination, is limited to groups of control entities whose sizes and compositions may in turn be adjusted to the system conditions. The second and third items deal with event-based time-varying communication structures that should be handled by the controller, sharing some characteristics with the works of the first group.

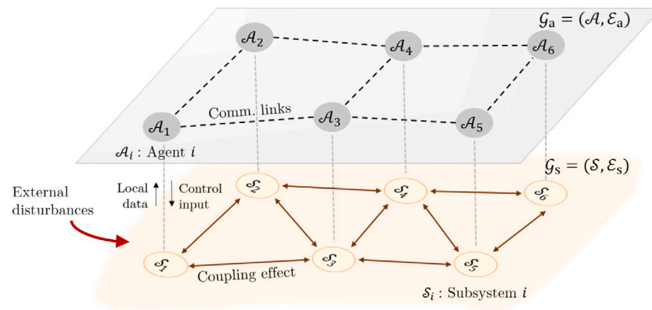

Fig. 1. Scheme of a distributed system composed of 6 subsystems that are assigned to a set of networked agents. Graph $\mathcal{G}_s = (\mathcal{S}, \mathcal{E}_s)$, which models the inter-subsystems coupling relations, is represented with solid red arrows. On the other hand, the control communication network, modeled by graph $\mathcal{G}_a = (\mathcal{A}, \mathcal{E}_a)$, is shown in black dashed lines.

The rest of the paper is organized as follows. Section 2 presents a general description of the structure of distributed systems and their underlying communication network. Section 3 introduces different control approaches with the above-mentioned characteristics. In particular, we focus on *sparsity-promoting* control, *community-detection* methods, *coalitional* control, *time-varying partitioning*, *plug-and-play* architectures, and other controllers that similarly operate in presence of *switching topologies*. Section 4 focuses on the criteria determining the communication structure, its dynamic or static nature, and on the control architecture. Likewise, a summary of relevant theoretical properties is given. Section 5 provides a review of applications, with emphasis on those associated with power, water, and vehicle systems, renewable energy, and chemical processes. Finally, Section 6 suggests future research opportunities by describing some open issues and challenges.

2. System description

In distributed systems, the overall dynamics are typically modeled as an aggregation of M coupled subsystems, here denoted as $\mathcal{S}_1, \mathcal{S}_2, \ldots, \mathcal{S}_M$, which are managed by a network of control agents (see Fig. 1). In this setting, the system structure can be modeled by a graph $\mathcal{G}_s = (\mathcal{S}, \mathcal{E}_s)$, where the set of nodes $\mathcal{S} = \{\mathcal{S}_1, \ldots, \mathcal{S}_M\}$ represents the different subsystems and the set of edges $\mathcal{E}_s$ models the coupling relations. The network of controllers is also modeled by graph $\mathcal{G}_a = (\mathcal{A}, \mathcal{E}_a)$, where $\mathcal{A} = \{\mathcal{A}_1, \ldots, \mathcal{A}_M\}$ represents the set of agents and $\mathcal{E}_a$ contains the communication links that allow them to exchange data, and hence to coordinate their decisions. Note that the links in graph $\mathcal{G}_a$ does not necessarily coincide with those of $\mathcal{G}_s$, possibly restricting the information available to each local controller and the overall coordination capacity of the distributed system.

Different mathematical models are used to describe the subsystems dynamics and their interactions. For linear processes, the following state-space representation has been extensively used:

$$\begin{aligned} x_i(k+1) &= A_{ii}x_i(k) + B_{ii}u_i(k) + w_i(k), \\ w_i(k) &= \sum_{j \in \mathcal{N}_i} \left[A_{ij}x_j(k) + B_{ij}u_j(k)\right] + d_i(k), \end{aligned} \tag{1}$$

where x_i and u_i and are respectively the state and input vectors of subsystem i, and w_i is a vector of *disturbances* that captures both the possible external perturbations, i.e., d_i, and the coupling effect of neighboring subsystems, i.e., $\sum_{j\in\mathcal{N}_i}\left[A_{ij}x_j(k) + B_{ij}u_j(k)\right]$. In this respect, the set of neighbors is defined as $\mathcal{N}_i = \{j \in \mathcal{S} \setminus \{i\} \mid [A_{ij}, B_{ij}] \neq \mathbf{0}\}$. Note that *subsystem i* and *agent i* refer respectively to $\mathcal{S}_i$ and $\mathcal{A}_i$. Also, notice that by aggregating model (1) for all subsystems $i \in \mathcal{S}$, the overall system behavior can be modeled as

$$x(k+1) = Ax(k) + Bu(k) + d(k), \tag{2}$$

where $x = [x_i]_{i\in S}$, $u = [u_i]_{i\in S}$ and $d = [d_i]_{i\in S}$ are respectively the global state, input, and external disturbances vectors. Additionally, the global matrices are given by $A = (A_{ij})_{i,j\in S}$ and $B = (B_{ij})_{i,j\in S}$. This type of linear multi-agent system arises in many practical applications. For example, Zheng et al. (2018) presents a multi-zone building temperature regulation system where each zone's temperature is modeled as (1), being the thermal transfers the cause of coupling; Ocampo-Martinez et al. (2011) describes a large drinking water network by a model with the form of (2); and Dörfler et al. (2014) employs a continuous-time version of (2) to model a power network with several interconnected generators.

Other works such as Chanfreut, Maestre, and Camacho (2020a), Li, Tang, Li, Peeta, He, and Wang (2018), Lucia, Kögel, and Findeisen (2015), Masero, Frejo, Maestre, and Camacho (2021), Pourkargar, Almansoori, and Daoutidis (2017a, 2017b) deal with nonlinear systems that can be similarly decomposed into interconnected subsystems, which are modeled as follows:

$$x_i(k+1) = f_i(x(k), u(k), d(k)), \tag{3}$$

being f_i a non-linear function mapping the global state, input and disturbances into the state of subsystem i. For example, this type of models has been employed for describing a reactor–separator process (Pourkargar et al., 2017b), to capture the traffic dynamic along freeways (Chanfreut et al., 2020a), to model solar-through plants (Masero et al., 2021), and for describing consensus-based vehicle platoons (Li et al., 2018).

Notice that, besides inputs–states interactions as in (1) and (3), there may exist other coupling sources connecting the subsystems' dynamics and the agents' control problems. In this regard, see Negenborn and Maestre (2014) for a survey on distributed model predictive control (DMPC) methods where several multi-agent systems are classified according to whether coupling stems from constraints, control objective, inputs, outputs or states variables.

Finally, see Fig. 2 for an illustrative representation of the state-dependent need for input coordination between distributed agents. In particular, Fig. 2 shows the centralized and decentralized explicit MPC regions resulting from a small example with two input-coupled subsystems, characterized by states x_1 and x_2, whose agents manipulate respectively inputs u_1 and u_2. This figure was obtained using a prediction horizon of 6 time steps, inputs constraints $-2.5 \le u_1, u_2 \le 2.5$, state constraints $-6 \le x_1, x_2 \le 6$, and a quadratic objective function defined as $\sum_{k=0}^{N}\sum_{i=1,2}\left(\|x_i(k+1)\|_2^2 + 0.1\|u_i(k)\|_2^2\right)$.

3. Controller design procedure

This section describes different control approaches which, under different names, share the common objective of increasing the scalability, flexibility, and/or the modularity of the distributed control architecture, especially those that adapt the controller structure using sparse communication topologies. A relevant issue here is the blurry difference between static partitioning methods and clustering approaches involving a time-varying system decomposition and/or a dynamic aggregation of control units into communication components, e.g., Barreiro-Gomez, Ocampo-Martinez, and Quijano (2019), Fele et al. (2017), La Bella, Klaus, Ferrari-Trecate, and Scattolini (2021). Even when it is possible to consider them as separated fields, the methods employed overlap, making the differences more apparent than real. For this reason, this survey also brings into consideration multiple works from the system partitioning literature as will be seen hereafter.

3.1. Sparsity-promoting controllers

This approach includes a set of controllers that reduce the number of communication links by inducing a *sparse* structure of the controller matrices. In this context, works as Babazadeh and Nobakhti (2016), Dörfler et al. (2014), Fardad, Lin, and Jovanović (2011), Furieri, Zheng, Papachristodoulou, and Kamgarpour (2020), Jain, Chakrabortty, and

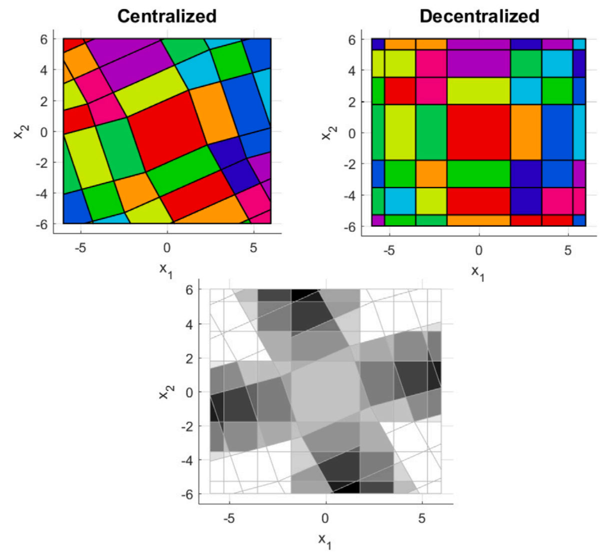

Fig. 2. Explicit MPC regions for a discrete time system with two input-coupled subsystems defined by (1) with A_{11}=A_{22}=1, $B_{11}=B_{22}=0.7$, and $B_{12}=-0.21$, $B_{21}=0.35$. In the decentralized subplot, subsystems 1 and 2 neglect respectively the effect of B_{12} and B_{21}. The black and white subplot illustrates the difference in the *optimal* inputs between the centralized and decentralized computation, with the darker zones indicating greater mismatches. Note that the light zones may also be associated to states where the inputs are saturated both in centralized and decentralized mode.

Biyik (2017), Lian et al. (2017), Lian, Chakrabortty, Wu, and Duel-Hallen (2018), Lian, Duel-Hallen, and Chakrabortty (2014, 2016), Lin, Fardad, and Jovanovic (2011), Lin et al. (2013), Wu and Jovanović (2014) consider a class of networked linear systems where the global input is defined as

$$u = -Kx, \tag{4}$$

being x and u the aggregates of the nodes' states and inputs, respectively, and K a feedback gain whose structure is given by

$$K = \begin{bmatrix} K_{11} & K_{12} & \dots & K_{1M} \\ K_{21} & K_{22} & \dots & K_{2M} \\ \vdots & & \ddots & \vdots \\ K_{M1} & K_{M2} & \dots & K_{MM} \end{bmatrix}, \tag{5}$$

where the sub-block K_{ij} represents feedback of the state of network node j to the control inputs of node i. Therefore, any $K_{ij} = 0$ with $i \ne j$ eliminates the need for inter-node data exchange, and thus the need for a communication link between i and j. Considering this, K is designed to minimize the two-fold function:

$$\mathcal{J}(K) = \underbrace{J(K)}_{\substack{\text{System}\\\text{performance}}} + \underbrace{\gamma g(K)}_{\substack{\text{Sparsity-promoting}\\\text{penalty}}}, \tag{6}$$

where $J(K)$ is a function measuring the closed-loop performance, $g(K)$ is a sparsity-promoting penalty that penalizes the number of state–input pairs, and γ is a non-negative weight that regulates the emphasis on the sparsity of gain K.

Special attention has been paid to the case of linear networked systems in which $J(K)$ is defined as an $\mathcal{H}_2$-measure (Zhou, Doyle, Glover, et al., 1996) of the closed-loop dynamics, leading to the trace minimization of a product of matrices involving K (Babazadeh & Nobakhti, 2016; Dörfler et al., 2014; Fardad et al., 2011; Fardad, Lin, & Jovanović, 2014; Lin et al., 2011, 2013; Wu & Jovanović, 2014). Different procedures have been proposed for obtaining such sparse feedback K, including a two-steps design method where the sparsity pattern of K is first determined by using the alternate direction method of multipliers (ADMM), and, subsequently, a closed-loop $\mathcal{H}_2$-norm is optimized to obtain the feedback entries (Lin et al., 2013); and an iterative

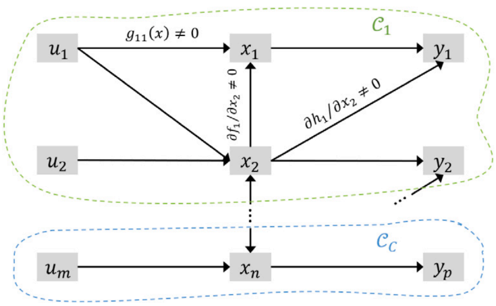

Fig. 3. Equation graph of a dynamical system described by $\dot{x}_i = f_i(x) + \sum_{j=1}^{m} g_{ij} u_j$ and $y_i = h_i(x)$, where f_i, g_{ij} and h_i are time invariant functions, m is the number of system inputs, n the number of states and p the number of outputs. Any state–state, state–output or input–state dependence in the model equations translates into an edge in the graph (Jogwar & Daoutidis, 2017).

design algorithm based on iterative convex optimization subproblems with LMI constraints (Babazadeh & Nobakhti, 2016). While most of the works focus on continuous-time models, discrete-time representations are employed in Fardad et al. (2014), Guicherd et al. (2020), Jain et al. (2017), Viegas, Batista, Oliveira, and Silvestre (2020). See for example Fardad et al. (2014), which proposes an $\mathcal{H}_2$-norm-based design procedure that isolates the related nonconvexities in one nonconvex matrix inequality; and Guicherd et al. (2020), where a sparse gain K is dynamically updated through a state-dependent optimization with linear and bilinear matrix inequalities. Also, examples of sparsity-promoting *output* feedback controller are given in Wu and Jovanović (2017) and Pajic et al. (2011).

3.2. Community detection

It is a graph partitioning method that divides the set of networked nodes into groups called communities, so that the nodes belonging to the same community are more densely connected than with those in external communities (Jogwar, 2019; Jogwar & Daoutidis, 2017; Pourkargar et al., 2017a, 2017b; Pourkargar, Moharir, Almansoori, & Daoutidis, 2019; Segovia, Puig, Duviella, & Etienne, 2021; Tang, Allman, Pourkargar, & Daoutidis, 2018). The criterion used to build the graph on which partitioning is applied varies but generally captures relevant system information to optimize the system decomposition and the corresponding controller structure. See for example Jogwar and Daoutidis (2017), where, as shown in Fig. 3, the system model equations are represented in graph form by assigning a node to each system input, state, and output, and using the edges to represent the structural relations between them. Such a graph is partitioned into groups of variables as disconnected as possible, which are subsequently assigned to a set of local sub-controllers. Similarly, Tang et al. (2018) uses a graph based on the relations between variables in the problem constraints; and Segovia et al. (2021) defines the communities by exploiting the matrix associated with the KKT conditions. A typical criterion for selecting the communities is the so-called *modularity*, which, as defined in Clauset, Newman, and Moore (2004), is given by

$$M = \frac{1}{2m} \sum_{i,j} \left(a_{ij} - \frac{k_i k_j}{2m} \right) \delta_{ij}, \tag{7}$$

where m is the total number of edges in the graph, a_{ij} is the (i,j) element of the adjacency matrix, k_i and k_j denote the total number of the edges connecting nodes i and j with the rest of the network, respectively, and δ_{ij} is a binary variable that is equal to 1 if nodes i and j belong to the same community, and 0 otherwise. Note that indexes i and j in Eq. (7), together with the mentioned adjacency matrix and variables k_i and k_j, are associated to the chosen graph representation, e.g., the one in Fig. 3 in the case of Jogwar and Daoutidis (2017). Conceptually, modularity measures the quality of a graph partition by weighting the number of edges that fall within communities against those that fall between them. In this regard, note that, although information sharing between coupled sub-controllers may be allowed, this network decomposition minimizes the need for cooperation. This approach is also employed in Pourkargar et al. (2017b), where different DMPC structures based on community decompositions are shown to provide close to optimal centralized performance while being more computationally efficient; and in Pourkargar et al. (2019), which presents an integrated DMPC control and estimation framework where community detection is used for both the controller and estimator design.

3.3. Coalitional control

The family of coalitional controllers (Baldivieso-Monasterios & Trodden, 2021; Chanfreut et al., 2020a; Chanfreut, Maestre, Muros, & Camacho, 2021; Chanfreut, Maestre, Zhu, & Camacho, 2020b; Fele, Debada, Maestre, & Camacho, 2018; Fele et al., 2017; Fele, Maestre, Hashemy, de la Peña, & Camacho, 2014; Maestre, Muñoz de la Peña, Jiménez Losada, Algaba, & Camacho, 2014; Masero et al., 2021; Muros, Algaba, Maestre & Camacho, 2017a, 2017b; Muros, Maestre, Algaba, Alamo & Camacho, 2017) consider multi-agent systems interconnected by a configurable data-network, which separates them into disjoint communication components referred to as *coalitions* or *clusters*. In general, it is assumed that the inter-agents communication links can be dynamically enabled/disabled so as to minimize the following two-fold function:

$$\sum_{k=0}^{\infty} \left(\underbrace{\sum_{\mathcal{C}_i \in \mathcal{N}/\Lambda(k)} \ell_{\mathcal{C}_i}(k)}_{\substack{\text{Stage performance}\\ \text{cost}}} + \underbrace{f(\Lambda(k))}_{\substack{\text{Coordination}\\ \text{costs}}} \right), \tag{8}$$

which depends on both the sequence of control inputs and the sequence of communication topologies or, equivalently, of partitions into coalitions. In this regard, symbol Λ in (8) represents the topology of the data network and $\mathcal{N}/\Lambda = \{\mathcal{C}_i\}_{i\in[1,C]}$ is the induced partition, with C being the corresponding number of clusters. Also, $\ell_{\mathcal{C}_i}(\cdot)$ represents the stage performance index of coalition $\mathcal{C}_i$ and $f(\Lambda)$ weights the coordination costs associated with topology Λ.

Similarly to the sparsity-promoting state feedback controllers (Dörfler et al., 2014; Lin et al., 2013), in the coalitional approaches (Chanfreut et al., 2021; Maestre et al., 2014; Muros, et al., 2017a, 2017b; Muros, Maestre et al., 2017) a set of subsystems are controlled by a feedback gain with the form of (5) so as to optimize (8). In this case, the controller may switch between sparser and denser communication structures. In particular, by solving an optimization problem with LMI and structural constraints, a set of matrices K are computed offline for different communication scenarios (see Fig. 4), which later are dynamically selected during the system operation. Likewise, MPC coalitional controllers are presented in Baldivieso-Monasterios and Trodden (2021), Chanfreut et al. (2020a, 2020b), Fele et al. (2018, 2017, 2014) and Masero et al. (2021). In this context, the overall set of distributed agents is dynamically partitioned into clusters of entities that jointly coordinate their local actuation by solving *smaller* cluster-based MPC problems. With a different formulation, and inspired by cooperative game theory, the concept of coalition is also employed in Han, Morstyn, and McCulloch (2018), Marzband, Ardeshiri, Moafi, and Uppal (2017), Mei, Chen, Wang, and Kirtley (2019), Safdarian, Divshali, Baranauskas, Keski-Koukkari, and Kulmala (2021) and Nguyen and Le (2017) for smart-grids applications. See for example Marzband et al. (2017), where the authors propose a bi-level structure that allows the formation of coalitions of cooperative energy-districts to maximize their profit.

Table 1
Taxonomy of clustering strategies based on the design approach.

Sparsity-promoting controllers	Babazadeh and Nobakhti (2016), Dörfler et al. (2014), Fardad et al. (2011, 2014), Furieri et al. (2020), Guicherd et al. (2020), Jain et al. (2017), Jovanović and Dhingra (2016), Lian et al. (2017, 2018, 2014, 2016), Lin et al. (2011, 2013), Pajic et al. (2011), Schuler et al. (2014), Viegas et al. (2020), Wu and Jovanović (2014, 2017), Zheng, Mason and Papachristodoulou (2016)
Clusters/partitions-based methods	Coalitional control: Baldivieso-Monasterios and Trodden (2021), Chanfreut et al. (2020a, 2021, 2020b), Fele et al. (2018), Fele, Maestre, and Camacho (2015), Fele et al. (2017, 2014), Fletscher, Maestre, and Peroni (2018), Han et al. (2018), Maestre and Ishii (2017), Maestre, Lopez-Rodriguez, Muros, and Ocampo-Martinez (2021), Maestre et al. (2014), Marzband et al. (2017), Masero, Fletscher, and Maestre (2020), Masero et al. (2021), Masero, Maestre, Francisco and Camacho (2020), Maxim, Maestre, Caruntu, and Lazar (2019), Mei et al. (2019), Monasterios, Trodden, and Cannon (2019), Muros, et al. (2017a, 2017b), Muros, Maestre, Algaba, Alamo, and Camacho (2014), Muros, Maestre et al. (2017), Muros, Maestre, Ocampo-Martinez, Algaba, and Camacho (2018), Nguyen and Le (2017), Safdarian et al. (2021) Community detection: Jogwar (2019), Jogwar and Daoutidis (2017), Pourkargar et al. (2017a, 2017b, 2019), Segovia et al. (2021), Tang et al. (2018) Time-varying partitioning: Ananduta and Ocampo-Martinez (2019, 2021), Ananduta, Pippia, Ocampo-Martinez, Sijs, and De Schutter (2019), Barreiro-Gomez et al. (2019), Giudicianni, Herrera, di Nardo, Carravetta, Ramos, and Adeyeye (2020), Núñez, Ocampo-Martinez, Maestre, and De Schutter (2015), Rocha, Oliveira-Lopes, and Christofides (2018), Zhou, Lin, and Xi (2012) Others: Ali, Muyeen, Bizhani, and Ghosh (2020), Barreiro-Gomez (2019), Camacho, Sanchez del Pozo Fernandez, and Len (2019), Chakrabortty (2012), Che, Zhang, Shahidehpour, Alabdulwahab, and Abusorrah (2015), Cheng and Scherpen (2018), Fu, Liu, and Hu (2017), Guo, Hug, and Tonguz (2015), Ishizaki, Kashima, Imura, and Aihara (2013), Jadhav, Patne, and Guerrero (2018), Jia, Lu, Wang, Zhang, and Shen (2015), Jing, Bai, George, and Chakrabortty (2021), Kang, Tang, Liu, and Daoutidis (2016), La Bella et al. (2021), Ma, Chiu, and Yang (2009), Nayeripour et al. (2016), Ocampo-Martinez, Barcelli, Puig, and Bemporad (2012), Ocampo-Martinez et al. (2011), Sánchez, Gallego, Escaño, and Camacho (2019), Siniscalchi-Minna, Bianchi, Ocampo-Martinez, Domínguez-García, and De Schutter (2020), Xu, Ho, Li, and Cao (2015), Ye, et al. (2019), Zheng et al. (2018), Zhong et al. (2004), Zhou, De Schutter, Lin and Xi (2016)
Switching topologies	Abou Harfouch, Yuan, and Baldi (2017), Ahandani, Kharrati, Hashemzadeh, and Baradarannia (2020), di Bernardo et al. (2015), Chehardoli and Homaeinezhad (2018), Ding, Ge, Pan, and Wang (2016), Dong, Zhou, Ren, and Zhong (2016), Lai, Zhou, Lu, Yu, and Hu (2016), Li et al. (2020, 2018), Liu, Gu, Sheng, Meng, Xue, and Chen (2015), Lu et al. (2016), Moreau (2005), Olfati-Saber and Murray (2004), Ren and Beard (2005), Savino, dos Santos, Souza, Pimenta, de Oliveira, and Palhares (2015), Schiffer et al. (2017), Shi, Shi, and Zhang (2020), Wang, Feng, Li, and Yu (2017), Wei, Li and Wu (2020), Xiao and Wang (2008), Xue, Gusrialdi, and Hirche (2013), Zhang, Nguang and Yu (2017), Zhao, Dai, Zhang, and Ding (2020)
Plug-and-play	Alonso, Ho, and Maestre (2020), Bansal, Zeilinger, and Tomlin (2014), Hou, Li, and Zheng (2021), Hou, Zheng, and Li (2019), Liu et al. (2015), Lou, Gu, Xu, Cheng, and Liu (2016), Lucia et al. (2015), Riverso et al. (2016), Riverso, Farina, and Ferrari-Trecate (2013), Riverso et al. (2014), Riverso and Ferrari-Trecate (2015), Zeilinger, Pu, Riverso, Ferrari-Trecate, and Jones (2013), Zhou, Burns, Danielson and Di Cairano (2016)
Miscellaneous	Akashi, Ishii, and Cetinkaya (2018), Chen, Zhao, Xu, Liu, Zhu, and Shao (2020), Gao, Zheng, and Li (2018), Groß and Stursberg (2015), Han, Zhang, Li, Coelho, and Guerrero (2017), Jain, Chakrabortty, and Biyik (2018), Jalal and Rasmussen (2016), Lou et al. (2016), Sadi and Ergen (2017), Smith and Bullo (2009), Wei, Li and Zheng (2020), Zhang, Xu, Srinivasan and Yu (2017), Zheng, Li, Li, Borrelli and Hedrick (2016)

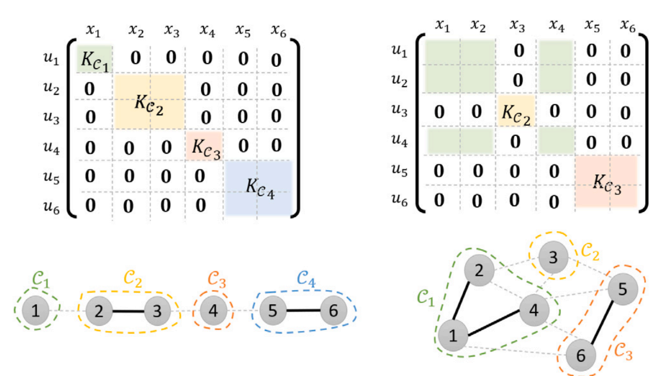

Fig. 4. Examples of sparse feedback gains for the sparsity-promoting controllers (Babazadeh & Nobakhti, 2016; Dörfler et al., 2014; Fardad et al., 2011; Lian et al., 2017; Lin et al., 2013; Wu & Jovanović, 2017) and coalitional approaches (Chanfreut et al., 2021; Maestre et al., 2014; Muros, et al., 2017a, 2017b; Muros, Maestre et al., 2017). At the bottom, two networks are partitioned into disconnected elements, which, by following the coalitional approach, have been marked as clusters and denoted as C_i. The figures at the top illustrates the structure of the resulting global feedback K and shows the corresponding input–state pairs. Note that all entries associated with disconnected nodes are forced to be zero.

3.4. Time-varying partitioning

Works as Barreiro-Gomez (2019), Barreiro-Gomez et al. (2019) and Ananduta et al. (2019) introduce partitioning approaches that aim to dynamically optimize the controller structure to reduce the computation and communication burden, while optimizing the system performance under time-varying conditions. In particular, Barreiro-Gomez et al. (2019) introduces a DMPC based on density-dependent population games that is combined with a dynamic partitioning algorithm. The latter, which can also be implemented in a distributed manner, uses a multi-objective goal that considers the number of links and the distance between different network partitions, the number of nodes in each partition, and a *relevance* index that assesses the impact of losing a given link. Likewise, Ananduta et al. (2019) presents an online partitioning method inspired by the static approaches in Barreiro-Gomez (2019), Ocampo-Martinez et al. (2011). In this case, the authors deal with a switching large-scale linear system controlled by a time-varying set of state-feedback local controllers, where a *central coordinator* manipulates the system partition and hence the corresponding feedback gains. Also, Ananduta and Ocampo-Martinez (2019, 2021) introduce *repartitioning* approaches for power networks where groups of self-sufficient, and locally controlled, microgrids are dynamically formed. Finally, see Zhou et al. (2012) and Giudicianni et al. (2020) for dynamic network partitioning methods in traffic and water distributions systems. Note that several of the works gathered in this category share similarities with the above-mentioned clusters-based and sparsity-promoting approaches, because they also search for an efficient control configuration by optimizing the system partition and its communication topology. However, they show significant differences. For example, in contrast to the coalitional methods proposed in Maestre et al. (2014) and Fele et al. (2017), in Ananduta et al. (2019), Barreiro-Gomez (2019), Barreiro-Gomez et al. (2019) and Ananduta and Ocampo-Martinez (2021) the subsystems and local agents definitions are updated online. Likewise, the problem is formulated as a graph-partitioning problem, thus also differing from the sparsity-promoting approaches, e.g., Dörfler et al. (2014), Lin et al.

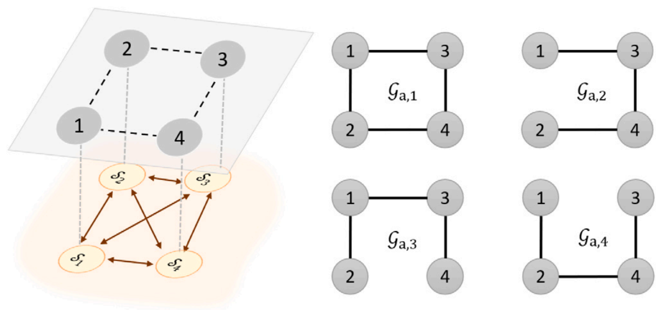

Fig. 5. Four different topologies of the dynamic communication network associated with the two-area-four machine system used in Schiffer et al. (2017). The solid black lines represent enabled communication links, and symbol $\mathcal{G}_{c,i}$ is used to denote different configurations.

(2013), which generally optimize the network by generating zeros in the controller matrices.

3.5. Unintentional switchings between communication topologies

Other works deal with distributed control networks where the communication topology among a set of distributed controllers switches over time for miscellaneous reasons, such as temporary communication losses or changes of the system structure (di Bernardo et al., 2015; Ding et al., 2016; Li et al., 2020; Lu et al., 2016; Schiffer et al., 2017; Smith & Bullo, 2009). For example, Ding et al. (2016) and Smith and Bullo (2009) consider a maximum inter-agent distance to enable effective communication for mobile agents coordination, thus leading to dynamic neighboring sets; Schiffer et al. (2017) addresses the frequency control problem in a power system that operates in presence of link failures and packet losses (see Fig. 5); and Li et al. (2020) and di Bernardo et al. (2015) deal with vehicle systems where switchings are triggered by incoming and outgoing cars and possible communication failures. Additionally, Olfati-Saber and Murray (2004), Ren and Beard (2005), Xiao and Wang (2008) and Savino et al. (2015) provide a theoretical analysis of consensus protocols in multi-agent systems where the data exchange is effected by switching topologies and/or time-varying delays; and Han et al. (2017) provides an overview of distributed control methods for micro-grids applications, where the switching nature of the communication structure is emphasized.

3.6. Controllers with plug-and-play capabilities

Works such as Bansal et al. (2014), Hou et al. (2021), Lucia et al. (2015), Riverso et al. (2016, 2013, 2014), Riverso and Ferrari-Trecate (2015), Zeilinger et al. (2013), Zhou, Burns et al. (2016) introduce distributed controllers where subsystems and agents can join or leave the overall system, leading also to time-varying interaction scenarios. In this context, Riverso and coauthors propose tube-based MPC approaches where agents can be designed by using only local and neighboring information, thus avoiding overall system knowledge and increasing the controller scalability (Riverso et al., 2013, 2014). These works are extended in Riverso et al. (2016), where a plug-and-play MPC for a class of non-linear systems is combined with a distributed fault detector to identify and isolate faulty agents, and in Zeilinger et al. (2013), which merges the plug-and-play capabilities of Riverso et al. (2013) with the distributed MPC in Conte, Voellmy, Zeilinger, Morari, and Jones (2012) so as to deal with strongly coupled systems. In this case, the authors introduce a transition phase after any plug-in or plug-out request, aiming at preparing the system for the network modification while avoiding feasibility losses and maintaining overall stability. Also, Bansal et al. (2014) extends the results of Zeilinger et al. (2013) to an application example. In particular, Bansal et al. (2014) deals with the integration of the charging of electric vehicles into the distribution network, and the connection/disconnection of the vehicles are treated as plug-and-play operations.

Table 1 provides a classification of the relevant works into the categories described before, including an additional entry to gather those approaches that do not directly fit in them but pursue similar objectives. For example, an *enhanced information reconfiguration DMPC* where the information structure between control agents varies dynamically as a function of the inter-agents coupling is proposed in Wei, Li and Zheng (2020); and, in Chen et al. (2020), subsystems are arranged into a hierarchical structure that determines the agents' interactions. Note that the categories in Table 1 are based on the terminology of the corresponding works. However, some terms and ideas can be shared by more than one category, e.g., a time-varying partitioning might fit into what it is referred to as coalitional control (Fele et al., 2017; Maestre et al., 2014). Additionally, Table 2 deals with the implemented control law, where we have focused on MPC, linear feedback gains, and consensus-based controllers because they are the most repeated among the strategies of Table 1. The rest of proposals have been gathered in the miscellaneous category.

4. Partitioning features

This section reviews different criteria for selecting and updating the controller structure and/or the system partition, with special emphasis on those based on computational and communication burden and network-induced constraints.

4.1. Partitioning criteria

Several works use a function to measure the benefits of different communication topologies. This index is subsequently used to induce the optimal agent partition, either offline, in case of static partitions, or online, when the partition can be occasionally updated. On the other hand, the network topology and coupling conditions may vary due to unpredicted events, e.g., links failures. Considering this, and to highlight particular features of different criteria, we introduce the subcategories described below (see also Table 3).

- *Penalty on the communication costs*: Clear examples are the previously mentioned sparsity-promoting controllers, e.g., Dörfler et al. (2014), Guicherd et al. (2020), Lin et al. (2013), where a feedback gain K is designed to provide a balance between system performance and network sparsity (6). The level of sparsity of K is measured by its *cardinality* or, equivalently, its ℓ_0-norm, i.e., the number of non-zero elements, however, the non-convex nature of the ℓ_0-norm has driven the use of ℓ_1-norm approximations as proxy for defining the sparsity-promoting penalty $g(K)$ (Babazadeh & Nobakhti, 2016; Dörfler et al., 2014; Fardad et al., 2011). Additionally, in Maestre et al. (2014), Muros, et al. (2017a), Muros, Maestre et al. (2017), a set of control agents are periodically partitioned into *coalitions* using an upper-bound on the cost-to-go and a coordination cost of the corresponding topology. Further examples are given in Baldivieso-Monasterios and Trodden (2021), where the agents partition is determined by a consensus-based iterative algorithm that considers an ancillary cost to penalize the formation of *big* clusters; and in Fele et al. (2018), where the control entities group autonomously to maximize their allocated benefit, which in turn depends on the balance between the clusters performance and the coordination costs.
- *Coupling strength:* Other works use the structural relations between system variables to find partitions as *disconnected* as possible. With this goal, Kang et al. (2016) uses the concept of *relative degree*, i.e., number of integrations required for some input to affect an output, as a measure of the system coupling. Also, in Zheng et al. (2018), a coupling degree-based clustering algorithm is

Table 2
Taxonomy of clustering strategies based on the control method.

MPC	Ahandani et al. (2020), Ananduta and Ocampo-Martinez (2019, 2021), Baldivieso-Monasterios and Trodden (2021), Bansal et al. (2014), Barreiro-Gomez et al. (2019), Camacho et al. (2019), Chanfreut et al. (2020a, 2020b), Chen et al. (2020), Ding et al. (2016), Fele et al. (2018, 2015, 2017, 2014), Fu et al. (2017), Gao et al. (2018), Groß and Stursberg (2015), Hou et al. (2021, 2019), Jain et al. (2018), Jalal and Rasmussen (2016), La Bella et al. (2021), Li et al. (2020), Lou et al. (2016), Lucia et al. (2015), Maestre and Ishii (2017), Masero, Fletscher et al. (2020), Masero et al. (2021), Masero, Maestre et al. (2020), Maxim et al. (2019), Monasterios et al. (2019), Muros et al. (2018), Núñez et al. (2015), Ocampo-Martinez et al. (2012, 2011), Pourkargar et al. (2017a, 2017b, 2019, 2019), Riverso et al. (2016, 2013, 2014), Riverso and Ferrari-Trecate (2015), Rocha et al. (2018), Sánchez et al. (2019), Segovia et al. (2021), Shi et al. (2020), Siniscalchi-Minna et al. (2020), Tang et al. (2018), Wang et al. (2017), Wei, Li and Wu (2020), Wei, Li and Zheng (2020), Ye, et al. (2019), Zeilinger et al. (2013), Zhao et al. (2020), Zheng, Li et al. (2016), Zheng et al. (2018), Zhou, Burns et al. (2016), Zhou, De Schutter et al. (2016)
State feedback gain	Akashi et al. (2018), Alonso et al. (2020), Ananduta et al. (2019), Babazadeh and Nobakhti (2016), Chanfreut et al. (2021), Dörfler et al. (2014), Fardad et al. (2011, 2014), Guicherd et al. (2020), Jain et al. (2017), Jing et al. (2021), Jovanović and Dhingra (2016), Lian et al. (2017, 2018, 2014, 2016), Lin et al. (2011, 2013), Maestre et al. (2021, 2014), Muros, et al. (2017a, 2017b), Muros et al. (2014), Muros, Maestre et al. (2017), Pajic et al. (2011), Schuler et al. (2014), Viegas et al. (2020), Xue et al. (2013), Zheng, Mason et al. (2016)
Consensus-based	di Bernardo et al. (2015), Chehardoli and Homaeinezhad (2018), Cheng and Scherpen (2018), Dong et al. (2016), Lai et al. (2016), Li et al. (2018), Liu et al. (2015), Moreau (2005), Olfati-Saber and Murray (2004), Ren and Beard (2005), Savino et al. (2015), Wu and Jovanović (2014, 2017), Xiao and Wang (2008), Xu et al. (2015), Zhang, Xu et al. (2017)
Miscellaneous	Abou Harfouch et al. (2017), Chakrabortty (2012), Furieri et al. (2020), Lu et al. (2016), Nayeripour et al. (2016), Sadi and Ergen (2017), Schiffer et al. (2017), Smith and Bullo (2009), Zhang, Nguang et al. (2017), Zheng, Li, Wang, Cao, and Li (2015)

Table 3
Taxonomy of clustering strategies based on the partitioning criteria.

Penalty on the costs of communication/coordination	Babazadeh and Nobakhti (2016), Baldivieso-Monasterios and Trodden (2021), Chanfreut et al. (2020a, 2021, 2020b), Dörfler et al. (2014), Fardad et al. (2011, 2014), Fele et al. (2018, 2015, 2017, 2014), Guicherd et al. (2020), Jovanović and Dhingra (2016), Lian et al. (2014, 2016), Lin et al. (2011, 2013), Maestre et al. (2014), Masero, Maestre et al. (2020), Muros, et al. (2017a, 2017b), Muros et al. (2014), Muros, Maestre et al. (2017), Núñez et al. (2015), Wu and Jovanović (2014, 2017), Xue et al. (2013)
Coupling strength	Ananduta et al. (2019), Chakrabortty (2012), Chen et al. (2020), Gao et al. (2018), Jalal and Rasmussen (2016), Jing et al. (2021), Jogwar (2019), Jogwar and Daoutidis (2017), Kang et al. (2016), Maxim et al. (2019), Ocampo-Martinez et al. (2012, 2011), Pourkargar et al. (2017a, 2017b, 2019), Rocha et al. (2018), Segovia et al. (2021), Siniscalchi-Minna et al. (2020), Tang et al. (2018), Wei, Li and Zheng (2020), Zheng et al. (2018)
Event-based criteria	Network constraints: Abou Harfouch et al. (2017, 2017), Ahandani et al. (2020), Alonso et al. (2020), di Bernardo et al. (2015), Chehardoli and Homaeinezhad (2018), Ding et al. (2016), Dong et al. (2016), Lai et al. (2016), Li et al. (2020), Liu et al. (2015), Lou et al. (2016), Lu et al. (2016), Moreau (2005), Olfati-Saber and Murray (2004), Pajic et al. (2011), Ren and Beard (2005), Savino et al. (2015), Schiffer et al. (2017), Shi et al. (2020), Smith and Bullo (2009), Xiao and Wang (2008), Zhang, Nguang et al. (2017), Zhao et al. (2020) Structural changes: Hou et al. (2021, 2019), Lou et al. (2016), Lucia et al. (2015), Riverso et al. (2016, 2013, 2014), Riverso and Ferrari-Trecate (2015), Wei, Li and Wu (2020), Zeilinger et al. (2013)
Application-based criteria	Ananduta and Ocampo-Martinez (2019, 2021), Camacho et al. (2019), Che et al. (2015), Cortes, Contreras, and Shahidehpour (2017), Cotilla-Sanchez et al. (2013), Giudicianni et al. (2020), Guo et al. (2015), Hajebi, Temate, Barrett, Clarke, and Clarke (2014), Jain et al. (2017, 2018), La Bella et al. (2021), Li, Liu, and Schneider (2010), Ma et al. (2009), Masero et al. (2021), Nayeripour et al. (2016), Sánchez et al. (2019), Ye, et al. (2019), Zhong et al. (2004), Zhou, De Schutter et al. (2016), Zhou et al. (2012)
Cooperative games-based criteria	Ali et al. (2020), Bauso (2021), Esfahani, Hariri, and Mohammed (2018), Fletscher et al. (2018), Han et al. (2018), Marzband et al. (2017), Mei et al. (2019), Nguyen and Le (2017), Safdarian et al. (2021)
Miscellaneous	Akashi et al. (2018), Ananduta et al. (2019), Bansal et al. (2014), Barreiro-Gomez et al. (2019), Chakrabortty (2012), Cheng and Scherpen (2018), Furieri et al. (2020), Han et al. (2017), Ishizaki et al. (2013), Li et al. (2018), Lian et al. (2017, 2018), Maestre and Ishii (2017), Schuler et al. (2014), Viegas et al. (2020), Wang et al. (2017), Xu et al. (2015), Zhang, Xu et al. (2017, 2017), Zheng, Mason et al. (2016), Zhou, Burns et al. (2016)

proposed, where the set of subsystems is partitioned into mid-scale subsystems whose elements are strongly coupled internally and weakly coupled with the rest of the system; and in Wei, Li and Zheng (2020), a set of local MPC agents dynamically decide the information topology by exploiting the concept of *impaction indices*, which in turn measure the coupling effect (see Fig. 6). Further examples are the community detection methods used in Jogwar (2019), Jogwar and Daoutidis (2017), Pourkargar et al. (2019), Segovia et al. (2021), Tang et al. (2018).

- *Event-based criteria*: We have placed within this category those works where the controller communication structure varies due to communication failures and/or plug-and-play operations. In both cases, from a local viewpoint, the availability of neighboring data is limited and varies in an event-based manner. The following subcategories are considered:
  - *Network constraints*: This case is associated with the proper functioning of the system communication resources and

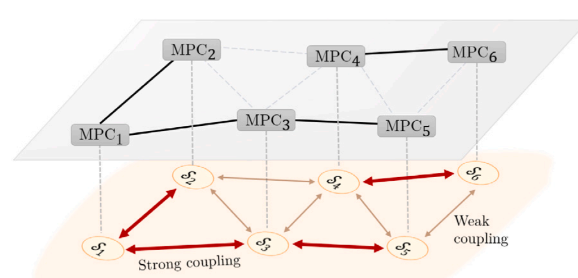

Fig. 6. Structure of the *information reconfiguration-based* DMPC (Wei, Li & Zheng, 2020) and of the *coupling degree clustering-based* DMPC (Zheng et al., 2018). In both cases, interactions among weakly coupled agents are reduced to a minimum, thus deterring unnecessary data exchange and coordination efforts.

similarly result in sparse and often dynamic interaction scenarios, e.g., topology switchings due to link failures (di Bernardo et al., 2015; Li et al., 2020; Lou et al., 2016; Lu et al., 2016; Olfati-Saber & Murray, 2004; Savino et al., 2015; Schiffer et al., 2017; Xue et al., 2013; Zhang, Nguang et al., 2017), communication delays (Olfati-Saber & Murray, 2004; Schiffer et al., 2017; Xiao & Wang, 2008; Zhang, Nguang et al., 2017), and due to changes in the arrangement of the agents that inhibit an effective exchange of data (Ding et al., 2016; Savino et al., 2015; Smith & Bullo, 2009).

- *System structural changes*: This subcategory is devoted for plug-and-play architectures (Bansal et al., 2014; Lou et al., 2016; Riverso et al., 2016, 2013, 2014; Riverso & Ferrari-Trecate, 2015; Zeilinger et al., 2013; Zhou, Burns et al., 2016), where the trigger for plug-in or plug-out operations may change, but always lead to an addition or removal of some subsystem and its corresponding agent.

• *Application-based criteria:* The controller configuration can follow particular characteristics of the system being controlled. For example, a multi-attribute partitioning method is proposed in Cotilla-Sanchez et al. (2013), where the goal is to design clusters that optimize a weighted sum of *electrical indexes* and other measures associated with the clusters sizes and inner connectedness. The concept of electric distances is also employed in Zhong et al. (2004). Other partitioning criteria are given in Jain et al. (2017, 2018), where the underlying communication topology of a power system is decided after a disturbance event according to the generators' influences on the inter-area oscillation modes excited by that disturbance. Additionally, Li et al. (2010) considers active and reactive power imbalances between the generated energy and loads in different areas of a power network, and Siniscalchi-Minna et al. (2020) proposes a mixed-integer partitioning problem for wind farms based on the wake effect among turbines. Note that some of these approaches are directly related to the coupling conditions in the system, but have been presented here because they are based on features of particular applications.

• *Cooperative-games-based criteria:* This subcategory gathers works using a game-theoretical formulation, where a set of decision-makers or *players* can form coalitions to maximize their profit. Note that the main difference with the so-called coalitional controllers in Chanfreut et al. (2020a), Fele et al. (2014), Masero et al. (2021) lies in the perspective and goals pursued, i.e., Ali et al. (2020), Bauso (2021), Esfahani et al. (2018), Fletscher et al. (2018), Han et al. (2018), Marzband et al. (2017), Mei et al. (2019) and Nguyen and Le (2017) consider a game characterized, among others, by a certain *transferable utility* that should be maximized by the players, while in Chanfreut et al. (2020a), Fele et al. (2014) and Masero et al. (2021) the coalitions represent clusters of MPC agents that independently optimize their inputs to balance the overall performance and cooperation efforts, without attending to the distribution of the corresponding benefits. The game-theoretical approach has been widely used for energy trading problems in electric systems. See Ali et al. (2020), Esfahani et al. (2018), Han et al. (2018), Marzband et al. (2017), Mei et al. (2019), where sets of microgrids can trade local power so as to satisfy their corresponding demands while optimizing economic costs. Further applications are given in Fletscher et al. (2018) and in Bauso (2021), which focus respectively on heterogeneous cellular networks and systems of multiple wind farms.

• *Miscellaneous*: Apart from the above-mentioned approaches, the literature covers further criteria, e.g., Lian et al. (2017) designs a sparse feedback controller as (5) by directly introducing a constraint on the number of non-zero off-diagonal elements in K; in Cheng and Scherpen (2018), the goal is to detect significant behavioral differences among different parts of a global system to cluster agents with similar behaviors; and Ananduta et al. (2019), apart from minimizing the coupling between system partitions, seeks to balance the number of inputs and states belonging to each of them.

All of these categories are summarized in Table 3.

4.2. Dynamic vs static partitioning

The works cited throughout this survey can be further categorized according to the dynamic or static nature of the proposed controller structure (see Table 5). While some approaches use a static sparse control configuration, which allows eliminating non-critical communication links, e.g., Lin et al. (2013), others propose time-varying structures where the topology of the communication network may switch due both to predicted and unpredicted events, e.g., to optimize a balance between performance and coordination (Baldivieso-Monasterios & Trodden, 2021), or to deal with link failures (Schiffer et al., 2017). While the former allows simplifying the complexity of the data network and the need for communication resources, dynamic configurations introduce an extra degree of flexibility that allows adapting the controller structure to the system needs. The possibility of manipulating in real-time the control configuration involves the introduction of new decision variables that increase the complexity of the problem as described in Fele et al. (2017), Guicherd et al. (2020) and La Bella et al. (2021). To mitigate this issue, works as Chanfreut et al. (2020a), Fele et al. (2014), Guicherd et al. (2020), La Bella et al. (2021) propose two-sample rate approaches where the agents' configuration is decided in a coarser time scale than control inputs, i.e., decisions on the controller structure are limited to specific time steps.

4.3. Control architecture

A distinct feature is the perspective for adjusting the control configuration in the case of the dynamic approaches (see Table 5). Broadly speaking, two different approaches have been adopted:

• *Top-down*: In some works, the decisions on the controller structure require complete system information and/or coordination, e.g., to evaluate a global metric or to solve an optimization problem involving overall variables and parameters, such as the global state in Guicherd et al. (2020), Maestre et al. (2014), the mixed-integer partitioning problem in Siniscalchi-Minna et al. (2020), or the forecasts on the system available resources in La Bella et al. (2021). Examples of this approach are those considering a supervisory entity as Guicherd et al. (2020), where a supervisory agent periodically updates the gain of a sparse feedback controller; Jain et al. (2018), which employs *central coordinator* to identify the most influencing controllers that should exchange data; and Chanfreut et al. (2020a), Fele et al. (2014), Masero et al. (2021), which propose hierarchical MPC architectures where a top layer periodically split the agents up into cooperative clusters.

• *Bottom-up*: Other works propose distributed approaches that eliminate the need for a central coordinator so that the control configuration selection is directly performed by the local entities. Peer-to-peer approaches are proposed in Baldivieso-Monasterios and Trodden (2021), where the formation of cooperative clusters of controllers result from a consensus-based negotiation among a set of local MPC agents; in Wei, Li and Zheng (2020), where a set of local MPC controllers autonomously reconfigure their communication topology when the operating point changes; and in Ananduta and Ocampo-Martinez (2019), which deals with electrical power network and proposes an online partitioning algorithm based on the cooperation of a set of connected microgrids. Additionally, those works where unintentional topology switchings are managed without the need of a central unit have been played within this category. See for example the plug-and-play architectures in Hou et al. (2021), Riverso et al. (2013, 2014), where the reconfiguration of the local agents only requires data exchange among neighboring entities.

Note that a centralized selection of the controller structure is compatible with a distributed and decentralized inputs computation. That is, once a certain structure is imposed, the local agents can decide their actions according to the chosen interaction scenario and communication constraints. A classification according to the above-mentioned architectures is given in Table 4.

4.4. Theoretical properties

The switching between communication topologies in control networks, and thus the changes in the information available to each distributed agent, may have a significant impact on the local control problems and decisions. It is well known that stability issues can arise when switchings are present, for they may destabilize the overall system, or lead to loss of feasibility, even when all the communication structures are stable. For these reasons, works addressing this problem are worth mentioning. On the other hand, the formation of time-varying clusters of cooperative controllers, together with the possible distribution of the corresponding benefits, results in a control problem that goes hand-in-hand with cooperative game theory. Hence theoretical properties characterizing this game are of special interest, e.g., the existence of a core where no group of controllers has an incentive to split up. Table 6 gathers works reporting results concerning the properties below:

- *Stability*: Several of the works listed in Table 6 present stability proofs based on Lyapunov theory and switching systems theory, e.g., Abou Harfouch et al. (2017), di Bernardo et al. (2015, 2015), Li et al. (2018), Liu et al. (2015), Shi et al. (2020), Zhang, Xu et al. (2017). See for example the pinning-based cooperative controller for microgrids in Liu et al. (2015), the consensus-based protocol in Li et al. (2018), and the cooperative adaptive cruise control application in Abou Harfouch et al. (2017). Likewise, within the framework of coalitional state-feedback controllers, Maestre et al. (2021) designs a common Lyapunov function for all possible communication topologies, while Maestre et al. (2014) guarantees stability proving that there exists a switching performance function that decreases in time. This approach is also considered in Chanfreut et al. (2021), Muros, et al. (2017b), Muros et al. (2014), Muros, Maestre et al. (2017). Also, by introducing additional constraints in the controller design, stability has been guaranteed in Li et al. (2020), Wang et al. (2017), and converge to tracked set points in Wei, Li and Zheng (2020). In particular, Li et al. (2020) presents a DMPC for a vehicle platooning problem where stability and convergence properties are based on the so-called *neighbor-deviation* and *self-deviation* penalties and constraints. Further examples are Lou et al. (2016), Lu et al. (2016), which propose distributed secondary controllers for voltage and frequency restoration in microgrids, and provide sufficient stability conditions while considering time-varying communication topologies, model uncertainties, and/or plug-and-play events; also, Jain et al. (2018) and Schiffer et al. (2017) provide respectively stability conditions for a DMPC strategy and a *distributed averaging*-based controller for power networks; and Guicherd et al. (2020) and Ananduta et al. (2019) use switching linear feedback controllers and guarantee stability under dwell-time constraints.
- *Constraints satisfaction*: To robustify the controller against variable neighboring information, some works consider tightened constraints sets in line with tube-based MPC approaches, e.g., Baldivieso-Monasterios and Trodden (2021), Masero, Maestre et al. (2020), Riverso et al. (2016, 2013, 2014). In this context, note that the switchings of communication topologies involve changes on the neighboring knowledge and hence on the local uncertainty. See for example Baldivieso-Monasterios and Trodden (2021), which proposes a robust coalitional MPC, based on the combination of a primary and a secondary MPC, and provides constraints satisfaction, recursive feasibility, and stability guarantees under a dwell time condition. Additionally, in Riverso et al. (2013, 2014), the plug-in of a certain subsystem triggers the redesign of part of the remaining local controllers, so that the local problems constraints are adjusted to deal with the coupling effect of the added subsystem. Although plug-out operations do not require the redesign of controllers, it can provide performance benefits as stated in Riverso et al. (2013, 2014). Also, in the case of the switching sparsity-promoting controller in Guicherd et al. (2020), the authors introduce the possibility of adding new LMIs constraints, based on Kothare, Balakrishnan, and Morari (1996), to satisfy input, state and output constraints.
- *Game-theoretical properties*: Game-theoretical solutions have received special attention to develop fair cost allocations mechanisms and to promote cooperative actions in smart-grids, e.g., Ali et al. (2020), Esfahani et al. (2018), Han et al. (2018), Jadhav et al. (2018), Mei et al. (2019), Safdarian et al. (2021). In this context, Han et al. (2018) presents a nucleolus-based allocation method and guarantees that the corresponding game is balanced, and that the proposed payoff imputation belongs to its core. Likewise, Nguyen and Le (2017) considers a balanced and subadditive game and seeks a trade-off between allocation stability and fairness, which weights the cost saving deviation among the players. Also, Jadhav et al. (2018) defines clusters of buyers microgrids and formulate a non-cooperative game that is proved to have a unique Nash Equilibrium. See also Marzband et al. (2017), which presents a coalitional game for distributed energy resources, and provides a comparison of Shapley, Nucleolus, and Merge and Split methods to allocate the profits resulting from collaboration; and Esfahani et al. (2018), where a hierarchical structure that considers a game-theoretic double-action mechanism for day-ahead market operations is presented. Additionally, Lian et al. (2017, 2014, 2016) present cost allocation algorithms, based on the Nash bargaining solution, in the context of sparsity promoting controllers. The division in costs is based on different requirements, including coupling with neighboring areas and inter-area feedback properties. Finally, within the framework of coalitional feedback controllers (Maestre et al., 2014), Muros and coauthors formulate a links-based game where the communication links between agents are treated as players, which, in turn, provide certain benefits from a control perspective (Muros, Maestre et al., 2017). In particular, LMI constraints on the Shapley value of the communication links are introduced, allowing for promoting the use of certain topologies and setting limits in the players' payoff. These results are extended in Muros, et al. (2017a) by using the Banzhaf value, and, also, Muros, et al. (2017b) introduces Harsanyi power solutions in a similar framework.

5. Applications

This section aims to provide an overview of representative applications, including those where the controller structure is optimized, either offline or online, to achieve certain goals, and those where the communication topology varies due to network failures, such as links losses (see Section 4). In particular, despite not being the only ones, we focus on those given in Table 7, i.e, power networks, water systems, vehicle systems, renewable energy applications, and chemical processes. Likewise, for a better illustration of these applications, the following subsections provide a brief description of the main approaches in the works gathered in Table 7.

Table 4
Taxonomy of clustering strategies based on the architecture.

Top-down	Ananduta et al. (2019), Chakrabortty (2012), Chanfreut et al. (2020a, 2021, 2020b), Che et al. (2015), Cheng and Scherpen (2018), Fele et al. (2014), Giudicianni et al. (2020), Guicherd et al. (2020), Jain et al. (2017, 2018), Jovanović and Dhingra (2016), La Bella et al. (2021), Maestre et al. (2021, 2014), Masero, Fletscher et al. (2020), Masero et al. (2021), Masero, Maestre et al. (2020), Muros, et al. (2017a, 2017b), Muros et al. (2014), Muros, Maestre et al. (2017), Núñez et al. (2015), Segovia et al. (2021), Siniscalchi-Minna et al. (2020), Viegas et al. (2020), Xue et al. (2013), Ye, et al. (2019), Zhong et al. (2004), Zhou, De Schutter et al. (2016)
Bottom-up	Ananduta and Ocampo-Martinez (2019), Baldivieso-Monasterios and Trodden (2021), di Bernardo et al. (2015), Ding et al. (2016), Fele et al. (2018, 2015), Hou et al. (2021), Li et al. (2020, 2018), Liu et al. (2015), Lou et al. (2016), Lu et al. (2016), Lucia et al. (2015), Maestre and Ishii (2017), Maxim et al. (2019), Riverso et al. (2016, 2013, 2014), Riverso and Ferrari-Trecate (2015), Wei, Li and Zheng (2020), Xiao and Wang (2008), Zhang, Xu et al. (2017), Zhou, Burns et al. (2016)

Table 5
Dynamic vs static partitions.

Static	Babazadeh and Nobakhti (2016), Chen et al. (2020), Dörfler et al. (2014), Fardad et al. (2011, 2014), Jing et al. (2021), Jogwar (2019), Jogwar and Daoutidis (2017), Kang et al. (2016), Lian et al. (2017, 2018, 2014), Lin et al. (2011, 2013), Muros et al. (2018), Nayeripour et al. (2016), Ocampo-Martinez et al. (2011), Schuler et al. (2014), Tang et al. (2018), Wu and Jovanović (2014, 2017), Zheng, Mason et al. (2016), Zheng et al. (2018)
Dynamic	Abou Harfouch et al. (2017), Ananduta and Ocampo-Martinez (2019), Ananduta et al. (2019), Baldivieso-Monasterios and Trodden (2021), Bansal et al. (2014), Barreiro-Gomez et al. (2019), di Bernardo et al. (2015), Chanfreut et al. (2020a, 2021, 2020b), Ding et al. (2016), Fele et al. (2018, 2015, 2017, 2014), Giudicianni et al. (2020), Guicherd et al. (2020), Hou et al. (2021), Jain et al. (2017, 2018), La Bella et al. (2021), Lai et al. (2016), Li et al. (2020), Liu et al. (2015), Lou et al. (2016), Lucia et al. (2015), Maestre et al. (2014), Marzband et al. (2017), Masero et al. (2021), Moreau (2005), Muros, et al. (2017a, 2017b), Muros, Maestre et al. (2017), Núñez et al. (2015), Olfati-Saber and Murray (2004), Pajic et al. (2011), Riverso et al. (2016, 2014), Rocha et al. (2018), Savino et al. (2015), Schiffer et al. (2017), Shi et al. (2020), Wang, Bian, Shladover, Wu, Li, and Barth (2019), Wang et al. (2017), Wei, Li and Wu (2020), Wei, Li and Zheng (2020), Xiao and Wang (2008), Xu et al. (2015), Xue et al. (2013), Ye, et al. (2019), Zeilinger et al. (2013), Zhang, Nguang et al. (2017), Zhang, Xu et al. (2017), Zhou, Burns et al. (2016), Zhou, De Schutter et al. (2016), Zhou et al. (2012)

Table 6
Theoretical properties of control by clustering methods.

Stability	Abou Harfouch et al. (2017), Ananduta et al. (2019), Baldivieso-Monasterios and Trodden (2021), Bansal et al. (2014), di Bernardo et al. (2015), Chen et al. (2020), Ding et al. (2016), Guicherd et al. (2020), Hou et al. (2021), Jain et al. (2017, 2018), Jing et al. (2021), Lai et al. (2016), Li et al. (2020, 2018), Liu et al. (2015), Lou et al. (2016), Lu et al. (2016), Lucia et al. (2015), Maestre et al. (2021, 2014), Moreau (2005), Pajic et al. (2011), Riverso et al. (2016, 2013, 2014), Schiffer et al. (2017), Shi et al. (2020), Wang et al. (2017), Wei, Li and Zheng (2020), Zeilinger et al. (2013), Zhang, Nguang et al. (2017), Zhang, Xu et al. (2017), Zheng et al. (2015)
Constraints satisfaction	Baldivieso-Monasterios and Trodden (2021), Guicherd et al. (2020), Masero, Maestre et al. (2020), Riverso et al. (2016, 2013, 2014)
Game-theoretical	Ali et al. (2020), Bauso (2021), Esfahani et al. (2018), Fletscher et al. (2018), Han et al. (2018), Jadhav et al. (2018), Lian et al. (2017, 2014, 2016), Marzband et al. (2017), Mei et al. (2019), Muros, et al. (2017a, 2017b), Muros, Maestre et al. (2017), Nguyen and Le (2017), Safdarian et al. (2021)

Table 7
Applications of control by clustering strategies.

Power networks	Ananduta and Ocampo-Martinez (2021), Ananduta et al. (2019), Chakrabortty (2012), Chen et al. (2020), Cheng and Scherpen (2018), Cortes et al. (2017), Cotilla-Sanchez et al. (2013), Dörfler et al. (2014), Fele et al. (2018), Guo et al. (2015), Hou et al. (2021), Jain et al. (2017, 2018), Lai et al. (2016), Li et al. (2010), Lian et al. (2017, 2014, 2016), Liu et al. (2015), Lou et al. (2016), Lu et al. (2016), Riverso et al. (2016, 2013, 2014), Riverso and Ferrari-Trecate (2015), Schiffer et al. (2017), Schuler et al. (2014), Wu and Jovanović (2014), Zeilinger et al. (2013), Zhong et al. (2004)
Water systems	Alvisi and Franchini (2014), Barreiro-Gomez et al. (2019), Diao, Zhou, and Rauch (2013), Eliades and Polycarpou (2012), Fele et al. (2014), Giudicianni et al. (2020), Groß and Stursberg (2015), Hajebi et al. (2014), Izquierdo, Herrera, Montalvo, and Pérez-García (2009), Jalal and Rasmussen (2016), Maestre et al. (2021), Masero, Maestre et al. (2020), Núñez et al. (2015), Ocampo-Martinez et al. (2012, 2011), Segovia et al. (2021), Wei, Li and Wu (2020), Wright, Stoianov, Parpas, Henderson, and King (2014), Wu, Liu, Wu, Liu, and Guan (2016)
Vehicle and traffic systems	Abou Harfouch et al. (2017), Bansal et al. (2014), di Bernardo et al. (2015), Chanfreut et al. (2020a), Chehardoli and Homaeinezhad (2018), Ding et al. (2016), Fardad et al. (2011), Fu et al. (2017), Jia et al. (2015), Li et al. (2020, 2018), Lin et al. (2011), Ma et al. (2009), Wang et al. (2019), Zhao et al. (2020), Zheng, Li et al. (2016), Zheng et al. (2015), Zhou, De Schutter et al. (2016), Zhou et al. (2012)
Renewable energy systems	Ananduta and Ocampo-Martinez (2019), Bauso (2021), Camacho et al. (2019), Che et al. (2015), Fele et al. (2017), Han et al. (2017), La Bella et al. (2021), Marzband et al. (2017), Masero et al. (2021), Nayeripour et al. (2016), Safdarian et al. (2021), Sánchez et al. (2019), Siniscalchi-Minna et al. (2020), Ye, et al. (2019)
Chemical processes	Jogwar (2019), Jogwar and Daoutidis (2017), Pourkargar et al. (2017a, 2017b, 2019), Rocha et al. (2018), Tang et al. (2018), Zhang, Nguang et al. (2017)
Others	Babazadeh and Nobakhti (2016), Dong et al. (2016), Fardad et al. (2014), Fletscher et al. (2018), Jing et al. (2021), Kang et al. (2016), Lin et al. (2013), Masero, Fletscher et al. (2020), Pajic et al. (2011), Savino et al. (2015), Smith and Bullo (2009), Wang et al. (2017), Zheng et al. (2018), Zhou, Burns et al. (2016)

5.1. Power networks

In recent years, increasing research efforts have been directed towards distributed control methods for power systems applications (Molzahn, et al., 2017). This approach has been driven by the advances in *wide-area* measurement systems and communication technologies, leading to the so-called *wide-area* control (WAC) (Chakrabortty & Khargonekar, 2013; Kamwa, Grondin, & Hébert, 2001). In this context, Chakrabortty (2012), Dörfler et al. (2014), Jain et al. (2017, 2018), Lian et al. (2017) present WAC designs for damping power oscillations in large networks. For example, Dörfler and coauthors design a sparse linear feedback controller whose performance is tested on the IEEE 39 New England power grid. In particular, the feedback gain in Dörfler et al. (2014) promotes a closed-loop dynamic similar to that of an ideal power system without inter-area oscillations, while reducing the need for communication links (see Section 3.1). Their results show that, even for high sparsity-promoting penalties, where practically all controllers operate by only accessing local variables, the performance degradation with respect to the optimal centralized case is 1.58%. Additionally, the system is simulated in presence of communication noise and delays to assess the robustness of the proposed strategy. The authors conclude that the sparsity-promoting controller not only reduces the communication requirements while yielding a good closed-loop performance, but also provides favorable robustness margins (Dörfler et al., 2014). The work of Dörfler et al. (2014) is extended in Lian et al. (2017), which presents a method to allocate the costs of communication among the distributed agents as a function of the related performance benefits. Also, in Jain et al. (2017), a set of generators are controlled by a sparse feedback gain whose structure is selected by a central coordinator after the occurrence of faults in the system. A similar framework is considered in Jain et al. (2018), but in the context of sparsity-promoting MPC. In this case, after a fault occurs, the central coordinator distributes the generators among a set of MPC controllers, which then send the control inputs to the corresponding local actuators. The proposal is tested on a 140-bus system with 48 generators that is perturbed with three-phase faults on different transmission lines, showing that it can effectively suppress the oscillations on the power output of all generators, while reaching sparsity levels of 75% and reducing by 70% the optimization times in comparison with the centralized MPC. Likewise, the authors illustrate numerically how the optimization times scale up as the number of generators managed by a single controller increases, e.g., a controller managing 3 generators required only 20% of the time needed to control a group of 10 generators. Note that the works of Dörfler et al. (2014) and Jain et al. (2018) use distinct indexes to evaluate performance and sparsity, but, essentially, they both assess the optimality of the system behavior and the number of communication links required. On the other hand, Chakrabortty (2012) proposes a clustering-based WAC design. In this case, the authors consider a three steps strategy, which roughly speaking consists of the following: the first step seeks to find clusters of coupled generators whose joint dynamic can be captured with a reduced order model; in the second one, a state feedback, based on these reduced-order models, is designed to provide a desired damping between any pair of clusters; and, in the last one, the feedback controller is *distributed* and tuned to the actual generators' local controllers. Also, Cotilla-Sanchez et al. (2013) proposes a multi-attribute partitioning method where the goal is to find the clusters that optimize a weighted sum of electrical indexes and other quality measures associated with the clusters sizes and the inner-clusters connectedness. The definition of this function is in turn based on an electrical *distance* metric that measures the marginal impact of active power transactions between network nodes on the corresponding voltage phase-angle differences. Results on the IEEE RTS-96, the IEEE 118-bus, and a 2383-bus case illustrate that the proposed partitioning method in Cotilla-Sanchez et al. (2013) can reduce transactions leakages, i.e., the impact of intrazonal transactions on the currents outside the zone, thus facilitating the application of zone-based planning and control schemes.

5.2. Water systems

To assist the control and management of water distribution networks, several works consider partitions into the so-called *district metered areas*, i.e., sub-networks of smaller size that can be independently managed by metering the water flows entering and leaving the area (Diao et al., 2013; Izquierdo et al., 2009). District metered areas approaches have been proposed with the goal of reducing leakages (Eliades & Polycarpou, 2012; Wu et al., 2016), improving system water resilience (Wright et al., 2014) and maximizing the recovery of energy (Giudicianni et al., 2020). In turn, this partition may be static or dynamic as in Wright et al. (2014) and Giudicianni et al. (2020). However, finding the optimal boundaries of each area is still a complex problem, especially in case of large-scale and highly looped water networks (Alvisi & Franchini, 2014; Diao et al., 2013; Wu et al., 2016). Note that, although in different contexts, the underlying idea of such partitioning shares notable similarities with that of the grouping methods for multi-agent systems proposed among others in Cheng and Scherpen (2018), Fele et al. (2017). For example, in Giudicianni et al. (2020), a water distribution network with 182 demanding nodes, 282 pipes and 2 sources is dynamically split up into district metered areas to maximize the recovered energy and reduce leakages, while also taking into account economic costs. In particular, the recovery of energy is based on the installation of micro-hydropower systems in the boundary pipes between district metered areas, which are points where water kinetic energy is shown to increase. In this regard, a clustering algorithm providing the size and shape of the clusters, and hence the corresponding set of boundary pipes, is employed. The authors report that the proposed partitioning approach generated annual net incomes of up to 4906€ in their simulations while bringing additional benefits, which include increased adaptability to different management tasks such as pressure management and leakage control, and the possibility of powering flow-meters and sensors using the recovered energy, thus also enhancing the system reliability. On the other hand, Ocampo-Martinez et al. (2011) presents a graph-theory-based partitioning approach for large-scale systems that is tested on the Barcelona drinking water network. In this case, the proposed method seeks to group together highly connected elements while balancing the partitions' sizes. Subsequently, a hierarchical partition-based DMPC strategy is proposed, where each controller can manipulate the transferred flows by acting on the corresponding pumps and valves. The simulation results show that the proposed partitioning-based controller provides a balance between performance, measured by water and electrical costs of the system operation, and computational time. In particular, the CPU time is reduced to approximately half of that of centralized MPC, at expense of a performance loss of about 15%. Similarly, in Fele et al. (2014), a hierarchical MPC for irrigation canals is proposed and simulated on a 13-reaches system where local controllers are dynamically merged into cooperative units, leading to time-varying and partial communication scenarios. The authors show that the number of variables managed by each of these cooperative units is reduced to one-sixth with respect to the centralized problem, thus reducing the optimization complexity. Likewise, it is illustrated that these cooperative units tend to arise when some stretch of the system is deviated from the desired setpoint, which reflects how the coordination burden is adjusted to the system needs.

5.3. Vehicles and traffic systems

Within the framework of automated driving systems (Guanetti, Kim, & Borrelli, 2018; Shladover, 2018), the last years have witnessed a growing interest in cooperative driving (Kianfar, et al., 2012; Wang et al., 2019), where the vehicles are equipped with onboard units, including sensors and wireless communication technologies, which enable the coordination of their decisions. As highlighted in Zheng et al. (2015), the information available to each car is often limited to a neighboring area due to range limitations of sensing and communication units, leading to partial communication scenarios. In turn, the inter-vehicle communication topology may vary over time due to the vehicles' movement (Ding et al., 2016), the possible entries and leavings of vehicles in the controlled system (Li et al., 2020), and communication failures that equally lead to information losses (Abou Harfouch et al., 2017; Li et al., 2020). In this context, Abou Harfouch et al. (2017), Li et al. (2020, 2018), Zheng et al. (2015) deal with vehicle platooning systems that operate in presence of switching topologies. The underlying goal of the platooning problem is to control a string of vehicles so that they travel at the same speed while maintaining a safe inter-vehicle distance between any pair of adjacent vehicles. In particular, Li et al. (2020) presents a DMPC, based on the approach of Zheng, Li et al. (2016), which guarantees overall stability and convergence of predicted terminal states despite the switching communication topologies among vehicles. The proposed DMPC is tested considering communication links failures and switching among frequent topologies in this kind of systems, e.g., the *predecessor following* topology, i.e., each car only receives data from its predecessor, and *leader–predecessor following*, i.e., also data from the leader is received. Likewise, a comparison with centralized MPC is provided, showing that the DMPC reduces the system performance by 24.50% in exchange for a lower communication burden and an increased scalability. See also Zheng et al. (2015) for a study on the influence of the communication topology on the stability and scalability of platoons, which includes the latter two scenarios. With a different approach Chanfreut et al. (2020a), Zhou, De Schutter et al. (2016) deal respectively with freeways and urban traffic networks, and propose two-level hierarchical predictive controllers based on dynamic decompositions into sub-networks. In particular, Chanfreut et al. (2020a) presents a coalitional MPC for traffic freeways based on a macroscopic model that captures the density of cars and the mean velocities in different stretches of the freeway. In this setting, each stretch is managed by a local controller that sets variable speed limits and manipulates the incoming on-ramp flows at the corresponding road section, while a supervisory layer promotes coordination between those stretches where the traffic situation is more critical. The results provided in Chanfreut et al. (2020a) show that the clustering approach provides a performance in-between that of centralized and decentralized MPC while reducing the time required for finding the control actions in comparison with the centralized case. As it is also illustrated in Fele et al. (2014) for water systems, the performance reduction is inversely related to the penalization of the coordination costs (see Eq. (8)), i.e., the lower this penalization is, the closer the performance is to the centralized case.

5.4. Renewable energy systems

In line with Section 5.1, distributed generation systems are gaining special relevance nowadays for the integration of renewable energy resources into the distribution network (Han et al., 2017). Note that Ananduta and Ocampo-Martinez (2019), Che et al. (2015), Fele et al. (2017), Han et al. (2017), La Bella et al. (2021), Nayeripour et al. (2016) are also associated with power networks but have been classified within this category due to their sharp focus on renewable energy resources. As an example, Nayeripour et al. (2016) introduces a zone-based approach for addressing the voltage regulation problem in distribution networks with geographically dispersed renewable generators. In this work, a method based on *particles swarm* optimization is proposed and compared with the interior point algorithm. The authors show that the proposed zone-based approach achieves the capability of online implementation, which was far from being possible using a centralized optimization. Additionally, as discussed in Che et al. (2015), Han et al. (2017), Liu et al. (2015), Lu et al. (2016), the interconnection and coordination of micro-grids systems provide significant advantages to increase the system reliability and optimize economic costs. Among others, grid areas with generation excesses may exchange power with those with deficient generation (see also Fele et al. (2017)), and share reserves to minimize the impact of possible generation interruptions or network disturbances. In particular, Che et al. (2015) proposes a probabilistic-based methodology for optimizing the network topology among a set of micro-grids, equipped with solar and/or wind energy resources, which considers the time-varying nature of the renewable generation, network uncertainties, system reliability, and economic costs. Likewise, La Bella et al. (2021) presents a clusters-based MPC controller that seeks to coordinate a set of distributed dispatchable and non-dispatchable generators to balance unexpected load variations with respect to predictions. In this case, clusters of generation and storage units are independently managed to match the corresponding demand fluctuations. If some of these partitions cannot guarantee a self-sufficient power balance, then, a supervisory layer sets inter-clusters power transfers to avoid shortages by using available power in other parts of the system. In this regard, the results show that the proposed architecture is able to compensate the variability between the clusters' demand and generation at each instant of the day, which implies that the power exchange with the main utility tracks the predicted evolution (La Bella et al., 2021).

Furthermore, Siniscalchi-Minna et al. (2020) introduces a non-centralized MPC for wind farms, where the total set of turbines are clustered into locally operated units. A central controller sets the power references of each subset to match the demanded power, which is subsequently distributed among the corresponding turbines. Their results show that the non-centralized MPC reduces the computational and communication demands concerning a centralized plant operation, while the performance decrease in terms of available power is lower than 1% (Siniscalchi-Minna et al., 2020). Additionally, Camacho et al. (2019), Sánchez et al. (2019) and Masero et al. (2021) propose clustering methods for solar parabolic-trough plants. In particular, by manipulating the loops valves, Sánchez and coauthors reduce temperature imbalances between different loops and thus avoid defocusing actions (Sánchez et al., 2019). The proposed approach combines a nonlinear MPC formulation with a clustering algorithm that minimizes the number of decision variables by grouping loops with similar efficiency. In this regard, the authors partition a set of 90 valves into 10 and 20 clusters, decreasing by 90% the maximum optimization times. Likewise, in Camacho et al. (2019), disturbances due to passing clouds are considered. Finally, see Masero et al. (2021), which presents a hierarchical coalitional MPC where coalitions of two loops are dynamically formed. The authors simulate the system under two solar direct normal irradiance profiles, reporting improvements of 0.79% and 1.10% in comparison with the case in which no valves are manipulated, whereas the improvements obtained with the centralized controller are 1% and 1.42%. In line with Chanfreut et al. (2020a), Fele et al. (2014), the results show a balance between computation time and global performance of the coalitional strategy when it is compared with centralized and decentralized MPC.

5.5. Chemical processes

Chemical processes have been frequently used to test community-detection-based partitioning methods, e.g., Jogwar (2019), Jogwar and Daoutidis (2017), Pourkargar et al. (2017b). These methods seek to find an optimal system decomposition, which is often considered static, for the implementation of a distributed control structure, such as the DMPC schemes in Pourkargar et al. (2017a, 2017b, 2019). In particular, Jogwar and Daoutidis (2017) provides results on several illustrative examples, i.e., three continuous stirred tank reactors, an energy-integrated solid oxide fuel cell system, a reactor–separator–recycle system, and a hydrodealkylation of toluene, while assessing the suitability of the system partitions according to the communities interactions. See also Tang et al. (2018), which proposes a constraints-based community detection method and provides results on a reactor–separator process. That is, in this case, variables sharing more constraints are grouped into the same communities, hence the constraints coupling between variables in different communities is minimized. Pourkargar et al. (2017b) considers a similar example and, in turn, presents a numerical comparison in terms of performance and computation times. Likewise, a combined community-based estimation and control architecture is presented in Pourkargar et al. (2019), where, as case study, a benzene alkylation process that comprises four continuous stirred-tank reactors and a flash tank separator is considered. Finally, Zhang, Nguang et al. (2017) uses a distinct approach, where the authors deal with communication constraint and topology switchings in the network interconnecting the plant sensors and actuators, and the corresponding controllers. In this case, the proposed control strategy, which considers event-based communication and an asynchronous controllers performance, is simulated on a continuous stirred-tank reactor.

6. Future research prospects

As has been shown in this article, a growing number of works and applications are consolidating the research area of distributed and networked control by clustering. The approach presents significant challenges that are likely to persist, and therefore provide interesting research opportunities. Some of these issues are briefly summarized below:

- *Heterogeneous systems*: The integration of agents with heterogeneous dynamics and computation capacities complicates the controller design beyond the challenges of varying communication networks and plug-in/out events. This situation may arise, for example, in vehicles platoons (Zheng, Li et al., 2016), where each vehicle is characterized, among others, by a corresponding mass, an aerodynamic drag, and certain constraints on the driving and braking torques, and may be equipped with distinct onboard units to communicate and compute control actions.
- *Cyber–physical systems*: Entities of diverse nature as robots and human beings can be active decision-makers (Baheti & Gill, 2011) in many practical applications, including smart grids (Cintuglu, Mohammed, Akkaya, & Uluagac, 2016), vehicle systems (Jia et al., 2015), and robotic systems (Nikolakis, Maratos, & Makris, 2019). In this context, the reliability and capacity of the data network play a key role to enable a proper functioning of the system, and hence the importance of also detecting and dealing with communication faults.
- *Theoretical properties*: In line with the previous item, providing guarantees regarding basic properties such as stability, robustness and performance bounds, and dealing with fundamental issues such as controllability and observability, remains a challenging task in distributed systems where the communication topology is time-varying, and, additionally, sparse. In this context, theoretical guarantees developed within the field of switching systems are of particular interest (Liberzon, 2003; Lin & Antsaklis, 2009).
- *Degree of suboptimality:* Clustering approaches adjust the inter-agents communication and coordination to balance performance, information exchange, and computation effort, generally involving a loss of optimality in comparison with centralized control. As a consequence, suboptimality bounds are of interest to quantify the degree of performance that is compromised.
- *Switching instants*: An inherent problem in time-varying partitioning schemes where the controller structure is intentionally changed, is deciding the switching instants. Although periodical solutions are shown to attain an efficient trade-off between performance and coordination costs, e.g., Fele et al. (2014), La Bella et al. (2021), further improvements could be achieved if the switching timing is optimized. Also, for MPC schemes, predicted changes of the control configuration could be integrated within the prediction horizon to implement a gradual transition between control configurations (Masero, Maestre et al., 2020).
- *Clustering problem:* Dealing with the combinatorial nature of the clustering problem is a significant challenge for a real-time implementation of cluster-based controllers, and, in particular, for those where the partition into clusters is dynamically generated. New methods to accelerate clustering decisions are expected. In this regard, artificial intelligence-based solutions could provide benefits and new prospects to address this problem, e.g., by *learning* from recorded system information.
- *Cyber-security and fault-tolerance:* Networked control architectures are vulnerable to cyber-attacks that can inject malicious software, which can originate non-compliant behavior in some local controllers. A similar problem can arise due to the faulty behavior of some system components. The additional flexibility of cluster-based approaches can be exploited to form groups of healthy controllers that facilitate the detection and isolation of unreliable agents and subsystems, thus mitigating the consequences of these events.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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