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Partitioning and Non-Centralized Optimization-Based Control for Large-Scale Complex Systems

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Contents

1 Introduction

The notion of large-scale systems (LSSs) refers to systems that consist of a large number of components, states, inputs, and/or outputs. Many critical infrastructure systems, such as electrical energy networks, water networks, and traffic networks, can be classified as LSSs. These systems are not only of large-scale nature but also geographically distributed in a large area. One of the main challenges faced when controlling LSSs is the complexity of computing control inputs especially when the available computational time and resources are limited. Moreover, a large amount of data, such as data from sensors or control inputs for the actuators, must also be communicated between the system and the controller. Additionally, for some LSSs, the reliability, the scalability, and the flexibility of the controller are also as important. Furthermore, some LSSs may also have additional features, such as uncertain behaviour of their components, effect of exogenous disturbances, and time-varying topologies, which increase the complexity of the control problem.

In dealing with the previously mentioned challenges, non-centralized approaches are perceived to be more suitable than the centralized counterpart, as discussed in [1, 2]. In a non-centralized approach, there exists a set of local controllers, in contrast to only a single central controller that is required in the centralized approach. Therefore, computational burden can be distributed to the local controllers. Furthermore, since each local controller can be assigned to a specific subset of sensors and actuators, it can be located near these instrumentation elements. Thus, the data communication can be more efficient and reliable than having a single controller, which implies all data must be sent to/from one location. Reported works [1, 2] also argue that non-centralized approaches have better reliability, scalability, and flexibility. For instance, when there is a failure in some part of the system or in some local controllers, the impact is local, implying the other parts may still work normally. Moreover, when there are changes, e.g., additional actuators or sensors are introduced, only some local controllers might need to be modified. In the centralized approach, failures and changes affect the whole system.

Model predictive control (MPC) is an extensively studied control technique [3, 4] that was initially developed into the industrial framework. In an MPC strategy, control inputs are computed by solving an optimization problem, which takes into account the dynamics of the system. Furthermore, as one of the main advantages of this framework, the operational constraints of the system may also be directly included into the optimization problem. Moreover, the control objective is presented as a cost function. Therefore, an MPC controller relies on the computational tools to solve the optimization problem. Although many optimization tools have been developed, applying an MPC controller efficiently, particularly to complex LSSs, is still an ongoing research topic.

In many non-centralized MPC approaches, a distributed optimization method is applied [2]. One of the advantages of such approaches is an optimal solution is obtained when the optimization problem must be solved is convex. In this regard, recent papers, e.g., [5,6], propose to apply tools from evolutionary game theory (EGT), namely population games and population dynamics [7], as distributed optimization methods. Thus non-centralized MPC controllers might be designed using this theory, as reported in [8]. However, [8] only discusses nominal systems while in reality, LSSs, such as infrastructure systems, have uncertainties/disturbances that must be taken into account. For instance, in the management of an electrical energy system, loads and power generation from renewable sources are uncertain. Therefore, one of the research topic in this thesis is to investigate how to extend the aforementioned non-centralized MPC method so that it can deal with systems with disturbances.

Prior to designing a non-centralized controller, an LSS must be partitioned into subsystems, to each of which a local controller is assigned. To that end, a system partitioning method, which is an automatic procedure to partition into subsystems, is applied. In most system partitioning methods, as discussed in Section 2, a graph-based representation is used to describe the system.

Thus, system partitioning can be considered as a graph partitioning problem [9]. In this regard, a graph partitioning technique can be applied. However, it is important to modify the technique so that the objectives of partitioning the system are achieved.

Furthermore, the complexity of the system must also be considered in the control design process. Besides disturbances, time-varying topologies are also one of the main issues that will be treated in this thesis. When a non-centralized MPC controller is applied to an LSS whose topology is time-varying, the controller must adapt to the topological changes. This implies the requirement of having a time-varying partitioning method as well as the readjustment of local controllers. Based on the current literature, time-varying system partitioning problems have not been discussed and methods to cope with such problems have not been developed. Therefore, such methods are going to be proposed based on the existing methods. Furthermore, the time-varying topologies and resultant partition might then affect the performances of the closed-loop system. Thus, it is also important to analyze the interaction between the time-varying partitioning methods that will be proposed and the closed-loop scheme based on the non-centralized controller.

On the other hand, some non-centralized MPC schemes, particularly the ones that are based on a distributed optimization method, require the subsystems to cooperate and exchange information through a communication network [1]. Therefore, it is important to ensure the reliability of the information exchange process. Some issues that might be found related to this process include communication link failures, which imply time-varying topology of the communication network, packet data losses, and delays [10]. Furthermore, the performance of the non-centralized MPC might also be affected by adversarial behaviors of some subsystems [11]. Hence, the controllers must be able to cope with these issues in order to guarantee that the closed-loop system performs as desired. In this regard, these issues will be investigated and techniques to improve the reliability of the control schemes against these issues will be proposed.

Electrical energy systems, e.g., power networks and microgrids, are also studied in this thesis and used as case studies since they can be considered as LSSs. In the current development of electrical energy grids, distributed generators and storages play an important role in the power generation. Furthermore, such systems may cover a large geographical area. Those features imply the necessity of a reliable non-centralized control method. Moreover, current electrical grids may also possess time-varying topologies. For instance, electrical vehicles, as ones of the components of the grid, move around and are connected to different charging points at different time instants. In this regard, energy management problems for such systems are seen as suitable control problems that are considered as case studies in this thesis. In addition, this is in line with the framework of innovative controls for renewable source integration into smart energy systems (INCITE[1]), under which this thesis is carried out. The INCITE project is a Marie Skłodowska-Curie European Training Network (ITN-ETN) funded by the HORIZON 2020 Programme. The goal of the project is to investigate new control algorithms with an integral view of the future electrical networks, including the energy management aspect.

In summary, the motivation of this thesis is to improve control techniques of complex LSSs, particularly within the energy field, and three-fold. Firstly, it aims to extend the non-centralized MPC approaches based on EGT such that they can be applied to a system with disturbances. Secondly, this thesis focuses on developing time-varying system partitioning methods in order to deal with time-varying behavior of the considered LSSs. Moreover, the influences of such partitioning methods to the non-centralized control approach that will be used are also analyzed. Finally, this thesis also deals with the resilience of the controlled system. In this regard, communication issues and information reliability will be treated and techniques to cope with these issues in the framework of non-centralized MPC will be proposed. Throughout the research, case studies in electrical energy systems are going to be considered.

[1] `http://www.incite-itn.eu/`

2 Literature Review

In this section, a literature review related to system partitioning and non-centralized MPC methods are presented. Furthermore, the dynamic optimal power flow problem, which is the application considered in this thesis, is also introduced.

2.1 System Partitioning

Partitioning methods for LSSs could already be found in some papers that were published in the 1980s. For instance, in [12], a state partitioning of linear time-invariant (LTI) systems, which uses the modal matrix that corresponds to the state-space model of the system, is proposed to design a suboptimal decentralized control. Since the early development of partitioning methods, graph theory has been used as the main tool. An LSS can be represented as a graph in which inputs, outputs, and states are considered as the vertices. Based on this representation, a partitioning algorithm is developed. The work of [13] decomposes non-linear systems into strong components with respect to the states based on the corresponding directed digraph. The graph-theoretic partitioning algorithm proposed in [14] partitions an LSS into a block-triangular interconnection of input reachable subsystems while the one of [15] results in input-output reachable subsystems. Furthermore, [16] introduces the nested ϵ-decomposition method, which considers the strength of the coupling between variables as the partitioning criterion. Graph-based algorithms have been continuously developed and many variations can be found. For instance, the work in [17] presents a graph-based partitioning method, which results in subsystems that have bordered block diagonal structure and are suitable to be controlled in a distributed fashion. Moreover, [18] presents a partitioning method that is inspired by the nested ϵ-decomposition and is applied to a real application, which is the Barcelona drinking water network.

The partitions obtained from the aforementioned partitioning methods are non-overlapping, which means that there are no inputs, outputs, nor states that belong to more than one partition (subsystem). However, in some cases, an overlapping partition, in which the resulting subsystems have some parts in common, might be required [19]. Multi-overlapping partitioning methods can be found for instance in [19], [20], [21], [22] and the references therein. The approaches in [19] and [20] are based on the inclusion principle and use non-singular expansion/contraction transformation matrices as well as permutation matrices. Similarly, the work in [21] partitions an LSS into pair-wise overlapping subsystems. In [22], the subsystems are simply obtained by collecting the states that are directly control by an input and their corresponding input as a subsystem. Overlapping decomposition can also be applied to hybrid systems, e.g., as shown in [23] and [24].

One of the objectives of partitioning is to obtain weakly coupled partitions. In this regard, some interaction measures have been developed. Relative Gain Array (RGA) [25], Hankel norm [26], as well as controllability and observability gramians [27] have been proposed as measures to determine input-output pairing. Furthermore, a partitioning method that is based on the Shapley value has also been proposed in [28]. According to these measures, partitions of LSS can be determined such that inputs and outputs from different subsystems have low interaction.

Based on the papers that have been surveyed, there is more interest in obtaining non-overlapping subsystems. Non-overlapping partitioning can also be seen as a graph partitioning problem. In the standard graph partitioning problem, a graph is divided into a number of subgraphs such that a vertex only belongs to a subgraph, the weights of the subgraphs are equal, and the cut size, *i.e.*, the number of edges with endpoints in different subgraphs, is minimized [29], [9]. However, the authors of [30] propose two different objectives that, in particular, are suitable for the partitioning of LSSs, namely open-loop performance metric and closed-loop optimal control performance of the system. The authors of [31] then extend the work in [30] into a multi-criteria optimization in order to allow a trade-off between the open-loop controllability criterion and the cost of the control.

In [9], graph-partitioning algorithms are classified into two classes. The first class is called the local improvement methods, which require an initial partition and then try to refine it, while the second class is called the global methods, which recursively partition a graph into a number of subgraphs. Furthermore, the third class, which is called multi-level methods, has also emerged. The algorithms that belong to this class have multiple steps, which combine a global method and a local improvement method [32].

A well-known local improvement method is the Kernighan-Lin algorithm [33]. In [34], a partitioning method, which is inspired by the Kernighan-Lin algorithm, is proposed to obtain the partition of the information-sharing network of a large-scale system that is controlled by a non-centralized controller. In this work, the objectives of the partition are not only to minimize the amount of links connecting different partitions and the difference of the amount of nodes in the partitions, but also to minimize the distance among the nodes in the same partition and the information relevance between different partitions.

On the other hand, bisection methods, in which a graph is divided into two subgraphs, are usually used as the main principle of some global methods, such as recursive and spectral bisection method. The work in [35] uses the spectral bisection method, which is recursively called, to partition large-scale biological systems in order to obtain a set of weakly interacting subsystems. Furthermore, the spectral bisection has also been effectively used to partition power networks, e.g., for emergency voltage control [36], [37], decentralized voltage regulation [38], and distributed optimal power flow [39]. Additionally, spectral bisection has also been proposed to be used to partition traffic systems in order to design signal control network [40].

In the multi-level algorithms, at first a global partitioning method is applied to get an initial partition; and then, a local improvement method is applied to refine the obtained initial partition. A preliminary step, which is called coarsening, is usually added [32]. In the coarsening step, the size of the graph is reduced while preserving some important properties that are necessary in the latter steps. Then, after an initial partition is obtained, an uncoarsening step is applied to recover the initial graph and finally the partition is refined.

The standard multi-level graph-partitioning algorithm has been applied to partition power networks [41], [42]. Furthermore, in [43], a multi-level graph partitioning that combines an ant algorithm and a genetic algorithm in the refining steps is proposed to partition a water network. Moreover, in [44], a multi-level partitioning algorithm that decomposes a general LSS is proposed. The algorithm in [44] is inspired by [32] with some additional refining steps. This algorithm is applied to Barcelona drinking water network and a hierarchical decentralized MPC is then designed and applied to control the partitioned network [44, 45]. Similar work can be found in [46]. However, the paper [46] proposes to use the sensitivity gain as the weights of the edges. Furthermore, in [47], another multi-level partitioning algorithm for large-scale systems is presented. In this algorithm, the initial partitioning is obtained by using the inputs as the center node of each subsystem. Moreover, in the step in which the number of vertices at each partition is balanced, the authors propose to use the dynamic performance matrix [30] as the stopping criterion of the algorithm.

Since system partitioning problems are in the class of combinatorial optimization problems, some general non-convex heuristic approaches have also been applied to solve them. Some examples are LSS partitioning based on a genetic algorithm [48], a tabu search method [49], and a harmony search method [50]. Genetic algorithms have also been used in some multi-level methods such as in [43] and [51]. In [52], two heuristics are proposed to partition transportation networks: one adopts a recursive iterative procedure to determine the network's sparsest cuts that maintain the balance and connectivity requirements, and the other one adopts a greedy network coarsening technique to determine the most independent subsystems. Moreover, a data-based partitioning method of discrete-event system models for fault diagnosis purposes has also been proposed in [53]. In addition, agglomerative methods can also be used to form partitions of a LSS, as shown in [54] and [55].

Table 1: Main Principles of the Partitioning Algorithms

Principle	**Algorithms**
Using a graph representation	[13], [14], [15], [16], [17], [18], [19], [20], [21]
Solving a graph partitioning problem	[28], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [49], [50], [51], [52]
Non-graph-based techniques	[12], [22], [23], [24], [30], [31], [48], [53], [54], [55]

Table 2: Techniques Used to Solve the Graph Partitioning Problem

Graph Partitioning Technique	**Algorithms**
Local improvement methods	[34]
Global methods	[35], [36], [37], [38], [39], [40], [49], [50], [52]
Multi-level methods	[28], [41], [42], [43], [44], [45], [46], [47], [51]

Table 3: Component Characteristics of the Resulting Sub-Systems

Characteristic	**Algorithms**
Overlapping	[16], [19], [20], [21], [23], [24]
Non-overlapping	[12], [13], [14], [15], [16], [17], [18], [22], [30], [31], [28], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [49], [50], [51], [52], [48], [53], [54], [55]

Table 4: Interconnections Between the Resulting Sub-Systems

Interconnection	**Algorithms**
Hierarchical	[13], [14], [15]
Non-hierarchical	[12], [16], [17], [18], [19], [20], [21], [22], [23], [24] [28], [30], [31], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [49], [50], [51], [52], [48], [53], [54], [55]

Table 5: Controller Structures

Controller Structure	**Algorithms**
Decentralized	[12], [13], [14], [15], [16], [17], [18], [19], [20], [23], [24], [30], [38], [46], [47], [55]
Distributed	[17], [21], [22], [28], [31], [34], [39], [44], [45], [48]

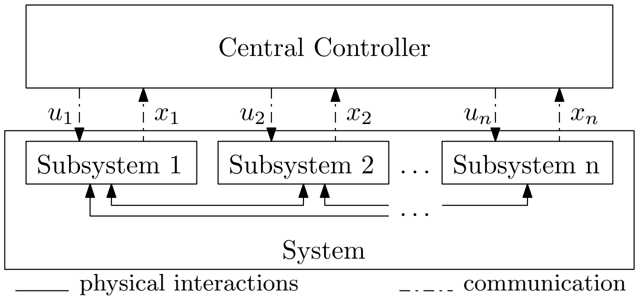

Figure 1: Centralized control scheme for a system that consists of n subsystems. The variable u_i and x_i, for $i = 1, 2, \ldots, n$, denote the control inputs and the states, respectively.

Some comparisons of the methods are provided in Tables 1-5. Although there have been many publications that discuss partitioning problems, it is found that none of them discusses online system partitioning approaches. Such approaches might be necessary when the topologies of the system has time-varying behavior. For instance, when the network topology is time-varying, the partition and the controllers may need to adapt in order to maintain the performance of the closed-loop system. Therefore, developing online partitioning approaches becomes one of the objectives of this thesis.

2.2 Non-Centralized Model Predictive Control

MPC is an optimization-based control method that computes its control inputs by minimizing a cost function while taking into account the dynamics of the system and operational constraints [4]. The controller requires the model of the systems in order to represent their dynamical behavior and a computational tool to solve the resultant optimization problems. Furthermore, an MPC controller takes into account the prediction over a certain time horizon and only applies the control input that corresponds to the current time instant. Additionally, it also applies the receding horizon principle, in which the prediction horizon is always shifted forward at each time instant.

This type of controllers has been studied extensively since it was introduced in the 1970s. The theory of MPC, particularly for linear systems, such as stability, feasibility, and optimality have been well developed [4, 56]. One of the research areas in MPC that has gained interest recently, and one of the focus of this thesis, is the design of non-centralized MPC controllers in order to deal with large-scale complex systems. In this section, a review on non-centralized MPC controllers, particularly those that are based on evolutionary game theory, is presented. Furthermore, as one of the research directions of this thesis, cyber perspective of such controllers is also discussed.

2.2.1 Description and Classification of Non-centralized MPC

In terms of control structures, MPC controllers can be categorized into centralized and non-centralized structures. As shown in Figure 1, a centralized control scheme has a single, central controller that controls the system. In this scheme, the controller must know the model and constraints of the whole system as well as connected to all sensors and actuators. On the other hand, non-centralized schemes consist of a set of controllers, each of which may only require partial model, constraints, and states as well as compute partial control inputs (see Figures 2 and 3). Non-centralized schemes are developed mainly to overcome issues faced by the centralized counterpart when the system is too large and complex [1, 2]. One of the issues is intractability, which is the inability of the controller to compute the control input in a given time due to the fact that the optimization problem behind the controller is too large or too complex. In this

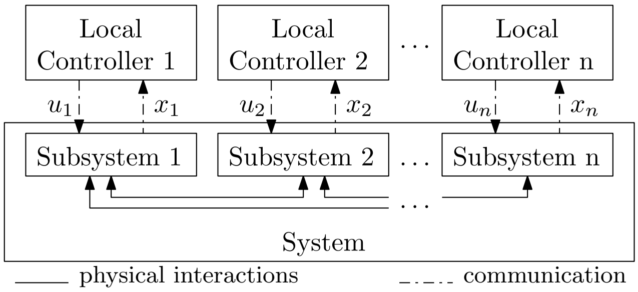

Figure 2: Decentralized control scheme.

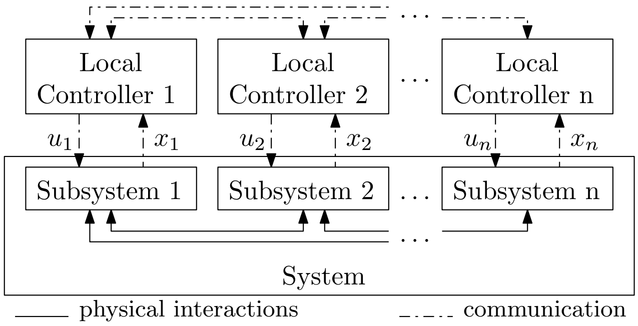

Figure 3: Distributed control scheme.

regard, by having a non-centralized scheme, the optimization problem can be decomposed into subproblems, which are locally tractable and assigned to the local controllers. Furthermore, as discussed in [1, 2], non-centralized schemes are more flexible and scalable than the centralized one. In terms of performance, the centralized control scheme is in general better, since it has the information of the whole system while in the non-centralized schemes, this is not the case. Nonetheless, many non-centralized approaches that are able to achieve quite similar performance as the centralized approach have been proposed (see [2] and [57] for a review of non-centralized approaches).

As presented in [1,2], non-centralized MPC approaches can be categorized into two categories, decentralized and distributed approaches. The main difference between these categories is the existence of communication among the local controllers. A non-centralized MPC is classified as a decentralized approach if the controllers do not communicate between each other, as shown in Figure 2. In contrast, a distributed approach require local controllers to share information among them, as shown in Figure 3. Communication is an important feature of distributed approaches since it allows local controllers to have extra information for computing the control inputs. Therefore, the performance of distributed approaches is in general better than the decentralized counterparts. In fact, most of non-centralized MPC approaches that are able to meet the centralized performance belong to the class of distributed approaches. However, decentralized controllers are relatively simpler than distributed ones while able to stabilize the system and/or achieve suboptimal performance that may still be enough for certain systems, e.g., weakly coupled systems [2].

The authors of [2] and [57,58] have reviewed and summarized many distributed MPC (DMPC) approaches that deal with different types of systems. Furthermore, there are many others that have been recently developed and are not covered in those reviews. In [57,58], some classifications are also made. These approaches are classified based on process features, such as coupling source; control features, such as architecture, controller knowledge and attitude, computation type, or communication; and theoretical features, such as optimality and robustness. In designing a DMPC scheme, it is important to identify the coupling source, i.e., what makes the overall system non-separable. There are five coupling sources, which are the objective, constraints, inputs, outputs, and states [58]. It is possible that there is more than one coupling source. Based on this knowledge and the control objectives, then some control features can be decided. For instance: whether the information required by each controller is strictly local, i.e., only the information of the neighboring subsystems, or partially global, i.e., some information of all subsystems; whether the attitude is cooperative or non-cooperative; and whether the communication between the controllers is serial or parallel.

The attitude of the controllers is implied from the algorithm of the approach. In non-cooperative DMPC algorithms, e.g., [59–61], each local controller minimizes a local cost function. On the other hand, cooperative algorithms, such as [62–64], minimize a global cost function. It is worth to mention that the concept of cooperation in this context is different than that from the game theoretical approach. Furthermore, DMPC algorithms can also be classified into iterative and non-iterative approaches, where the former refers to algorithms that evaluate the solutions multiple times while the later refers to algorithms that only evaluate the solutions once.

The focus of this thesis is on DMPC controllers that are based on a distributed optimization algorithm. Such control strategies can be classified into the class of cooperative approach. Although each controller minimizes a local cost function, in essence it cooperates with each other to optimize the global problem. In order to obtain the optimal solution, each subsystem has to exchange some information and update its solution, implying that the algorithm is iterative. Moreover, decomposition methods, such as primal or dual decomposition, can be applied to split the problem. Some DMPC approaches that are based on dual decomposition are proposed in [65–67]. Furthermore, the alternating direction method of multipliers (ADMM), which is an extension of dual decomposition, has also been applied as a DMPC method in [67]. Different approaches, in which the Karush-Kuhn-Tucker (KKT) optimality conditions are directly solved, have also been proposed. For instance, a DMPC scheme based on optimality condition decomposition (OCD) is presented in [68, 69].

The main advantage of DMPC controllers that are based on a distributed optimization method is the computed control inputs are optimal with respect to the whole system, as opposed to the non-cooperative approach, which seeks local optimal solutions. Furthermore, different than the cooperative approaches proposed in [62–64], in which each subsystem requires information from all the others, they only require local neighbor-to-neighbor communication. The main issue faced by this approach is to decompose the terminal cost function and terminal set constraints, which are necessary to guarantee stability of the closed-loop system and in general non-separable. A method to construct separable cost functions and novel time-varying terminal sets have been proposed to deal with this issue in [70].

2.2.2 DMPC based on Evolutionary Game Theory

Recently, distributed methods based on evolutionary game theory (EGT) are proposed to solve constrained optimization problems [5, 6]. Therefore, these methods can also be applied as distributed optimal controllers, as discussed in [6, 71]. EGT was first studied in the field of biology, when it was used to explain behaviors in nature. However, this theory is also applicable for engineering problems, including the control of multi-agent systems. Furthermore, the advantages of using EGT approach include straightforward analogies between games and many control problems, the existence of relationship between the solution of a game by a Nash equilibrium and of optimization problems, and the sufficiency of only using local information to obtain the solution of games, implying the possibility of using EGT as a distributed approach [71].

In EGT, population games model the interaction of large populations of agents [7]. Population games assume that all agents have the same set of strategies. The strategy profiles of these games are characterized by the distribution of agents among the strategies, denoted by population states. Moreover, a fitness function (payoff function) describes the reward obtained by agents when choosing a strategy. Population games also assume that all agents are rational, i.e., they try to maximize their payoff, implying the existence of a Nash equilibrium, i.e., each used strategy entails the maximum benefit for those agents that choose it. In order to maximize their benefit, agents need to change strategy. In doing so, they follow a revision protocol, which specifies the rules about when and how to choose new strategies. In this regard, the evolution of the population states is modeled by the population dynamics that are induced by the revision protocol that, in turn, is used in the game.

Two types of population games that are related to engineering optimization problems are full potential and stable games. A full potential game is a population game, the fitness functions of which are the derivative of a continuously differentiable potential function. The Nash equilibria of such games coincide with the extreme points of the corresponding potential function [7]. Furthermore, if a full potential game is stable, it is guaranteed that the output of the game is a Nash equilibrium. Therefore, a convex optimization problem might be described as a stable full potential game and population dynamics might be used as tools to solve the problem. Furthermore, distributed population dynamics (DPD) have also been derived from four of the most fundamental population dynamics, namely replicator, Smith, logit, and projection dynamics, allowing the emergence of EGT-based distributed optimization methods [6].

In [5,6], distributed optimal control methods have been designed using distributed population dynamics. Furthermore, the work in [8] also discusses the application of distributed population dynamics as DMPC approaches for nominal systems and the stability of the closed-loop system controlled by the proposed DMPC approach. However, this approach has not been applied to systems with disturbances. The fact that population games actually have stochastic behaviors might be used to design a stochastic DMPC approach based on EGT. In this regard, the stochastic evolutionary processes, especially in population games, are considered.

2.2.3 Cyber Perspective of DMPC

As previously discussed, DMPC methods require information sharing among local controllers in order to compute control inputs. In this regard, the reliability of the communication is important for any DMPC method so that local controllers receive information and perform as desired. In [10], several communication issues that might be found are discussed. The issues include delays, data-package drops, data-package disorder, and time-varying network topology, e.g., node and/or link failures or creation. These issues may lead to the failure of the controllers to compute optimal control inputs. The issues might be caused by system failures or cyber threats, e.g., malicious packet losses [72]. Recently, some papers have proposed solutions to deal with these communication issues for DMPC schemes. For instance, the work in [73] deals with delays in DMPC by using a robustness constraint and designing a waiting mechanism. Furthermore, solutions to improve the resilience of some DMPC methods against communication failures have also been proposed. The solutions include a scheme that assumes that the neighbor subsystems take null control inputs [74], substituting the coupled constraints with tube-based constraints that restrict the control inputs [75], and adding a robust observer [76].

Information reliability is not only guaranteed by the reliability of the communication network. Since in a DMPC method local controllers make their own decision, they must agree to cooperate in order to achieve an optimal performance in the perspective of the whole system. However, there might be cases when there are subsystems that are not willing to cooperate to gain advantages [11]. In doing so, they might share false and unreliable information to the other subsystems. The papers [11] and [77] discuss such problem in Lagrange-based DMPC and distributed optimization perspectives, respectively, and provide some solutions. In [11], the subsystems detect the largest and smallest control inputs that are shared and ignore the corresponding subsystems during the negotiation process. On the other hand, the authors of [77] propose an approach that exploits the trusted subsystems, i.e., subsystems that are known to act cooperatively, and constrains the solutions of the other normal subsystems to be bounded by the solutions given by the trusted subsystems.

2.3 Dynamic Optimal Power Flow Problems

Optimal power flow (OPF) problems are the core of an energy management system in power networks and/or other electrical energy systems. An OPF seeks optimal operating points that become the references of low level controllers. Many energy management problems are formulated as or derived from OPF. They include economic dispatch, unit commitment, reserve scheduling, among others.

The standard OPF problem only considers the static model of the power system [78]. However, storage systems, which have slow dynamics, are getting more frequently used in the current power systems. Moreover, electric vehicles, which can be perceived as moving storages, are expected to dominate the roads in the future. Therefore, it is now important to take into account the dynamics of the storages in the formulation of OPF problems.

The major changes of power systems are not only the penetration of storage systems, but also distributed generation, particularly renewable sources. Both factors make the problem more complex and computationally demanding. In this regard, distributed approaches are preferable since they can split the computational burden and offer more scalability, flexibility, safety than the centralized counterpart while maintaining the performance of the system.

The dynamic OPF of an AC electrical network can be casted as an optimization problem, the cost function of which is typically a quadratic generation cost [78]. However, in some OPF problems, the cost function may be defined differently, e.g., a loss cost, proximity cost to a voltage reference, or a combination of the aforementioned costs [78]. The minimization of the cost function is also subject to some constraints, which come from the modeling of the network. One of the main constraints is the power flow equation that is non-convex. A common approach to obtain a convex problem is by applying the DC power flow approximation, which assumes that reactive power flows can be neglected, the resistance of the lines is negligible, all voltage magnitudes are approximately equal, and the angle differences across the lines are small [78, 79]. Other operational constraints include the operational limits of the dispatchable distributed generators, voltage constraints on the network, and power flow limits. Furthermore, the dynamics of the storages can be represented as a linear state-space difference equation.

Many optimization problems for the energy management of power systems are derived from the standard OPF problem. When the power flow equations are disregarded, the standard OPF problem becomes an economic dispatch [79]. Furthermore, a unit-commitment problem refers to an economic dispatch problem that involves binary variables that represent the on/off status of the generators [80]. In a typical unit-commitment problem, the model of dispatchable generators is slightly modified into non-convex constraints that involve binary variables. Moreover, some additional constraints, such as start-up cost constraints, which add extra cost when turning on the generators, or constraints that ensures a generator stays on or off for at least some time instants, could also be added [80]. Another extension of the standard OPF problem is security-constrained OPF, in which possible contingencies and uncertainties are taken into account [81]. Additionally, a reserve scheduling problem deals with computing the power reserve that is required to avoid any disruption of service [80].

Research in developing methods to solve the standard OPF problem and its derivatives has been carried out extensively since 1960 [82]. Recently, distributed methods gain more attention since they are perceived to be more suitable with the current development of power systems, in which the penetration of distributed generation, particularly renewable sources, is increasing. As discussed in [78, 83], some distributed methods are based on augmented Lagrangian decomposition, e.g., the ADMM, Proximal Message Passing (PMP), Analytical Target Cascading (ATC), Auxiliary Problem Principle (APP), and Predictor Corrector Method of Multiplier (PCPM). Some other methods are based on the decentralized solution of the Karush-Kuhn-Tucker (KKT) necessary conditions for local optimality. These include Optimality Condition Decomposition (OCD) and Consensus+Innovation (C+I). Furthermore, there are also other methods, namely Gradient Dynamics and Dynamic Programming with Message Passing, that have been developed to solve the OPF problem. The paper [78] provides a survey of the aforementioned methods. Furthermore, [82] presents a comparison of APP, PCPM, and ADMM while [83] compares the performance of ADMM, PMP, ATC, APP, OCD, and C+I when solving an OPF problem with DC approximation.

The aforesaid distributed optimization methods may be extended to solve dynamic OPF problems. Furthermore, several DMPC approaches, some of which apply one of the previously mentioned distributed optimization methods, have also been proposed to deal with some dynamic energy management problems. Most of these approaches consider the DC approximation of the power flow equations. DMPC approaches based on OCD are proposed in [68, 69]. Unit-commitment problems of power systems with micro combined heat power generators, which are mixed-integer dynamic OPF problems, are solved by a dual-decomposition-based DMPC [84] and a multi-step DMPC in [85]. Other MPC-based distributed energy management of electrical networks with storages and distributed generators include: [86], in which a sequential and an iterative DMPC algorithms are applied; [87] and [88], in which ADMM-based algorithms are proposed; [89], which is based on game theory; [90], which uses a central entity that negotiates the market price of the electricity with the subsystems; and [91], which uses a distributed primal subgradient algorithm. However, a DMPC scheme that is based on EGT has not been proposed to solve a dynamic OPF problem. Note that, however, population dynamics have been proposed to solve static economic dispatch problems, e.g., in [71, 92]. Additionally, a more complex situation, e.g., when the topology of the electrical network is time-varying, has not been considered in the previous literature.

3 Objectives

General Objective

The general objective is to design partitioning methods and non-centralized optimization-based controllers for large-scale complex systems with time-varying topologies, specifically within the framework of power networks, while taking into account the interaction between the partitioning and the control approaches towards improving the closed-loop system performance.

Specific Objectives

1. Determine and propose partitioning methods that are suitable for systems with time-varying topologies.
2. Design non-centralized controllers based on evolutionary game theory (EGT) that are suitable for large-scale complex systems with time-varying topologies and disturbances.
3. Determine how the proposed time-varying partitioning approaches can be used to improve the performance of the closed-loop schemes controlled by non-centralized controllers proposed in item 2.
4. Investigate information-sharing issues related to the cyber perspective of DMPC controllers and improve the resilience of non-centralized control methods against information-sharing issues.
5. Apply the methodologies developed in items 1-4 to power networks and other related energy systems.

4 Methodology and Working Plan

4.1 Methodology

The methodology consists in deeply studying DMPC approaches, system partitioning, and evolutionary game theory. Therefore, the methodology is divided into three parts. Furthermore, energy management problems of electrical grids are also investigated as the main application of the control approaches and are considered in every part. Additionally, numerical simulations are used to justify theoretical results that are obtained.

In the first part, the focus is to study DMPC approaches that are based on a distributed optimization method. Optimality and stability are two key terms that are studied in this part. Additionally, an investigation of issues in DMPC from cyber perspective is carried out. Particularly, issues faced when the communication network is time-varying and when some local controllers show adversarial behaviors are analyzed and mitigated. In this regard, it has been identified that methodologies and theories from consensus problem can be explored as potential solutions.

The focuses of the second part are to study system partitioning and to develop partitioning methods that are suitable for systems that have time-varying topologies. In this part, graph theory, particularly the graph partitioning problem, plays an important role. Moreover, the interaction between time-varying partitioning methods and DMPC controllers is analyzed. The goal is to see whether one can improve the performance of the closed-loop system if such partitioning method is applied along with a DMPC method. Moreover, the stability of the closed-loop system must also be analyzed and guaranteed.

The last part is focused on exploring EGT and its application in DMPC. Since it has been identified that the existing EGT-based DMPC approaches work on nominal systems, it is interesting to extend these approaches to systems with disturbances. In this regard, the stochastic evolutionary processes, particularly in population games, will be explored.

4.2 Working Plan

In order to achieve the objectives stated in Section 3 and based on the methodology presented in Section 4.1, the tasks outlined below are formulated.

- **Task 1:** Literature review of non-centralized MPC methods.
- **Task 2:** Study on the impact of time-varying communication networks on DMPC schemes.
- **Task 3:** Literature review of large-scale system partitioning.
- **Task 4:** Exploration of existing partitioning methods for systems with time-varying topologies.
- **Task 5:** Stability analysis of time-varying partitioned systems with a non-centralized state-feedback control.
- **Task 6:** Literature review of dynamic OPF problems.
- **Task 7:** Thesis proposal preparation.
- **Task 8:** Investigation of methodologies to improve the resilience of DMPC methods against adversarial behaviors of some local controllers.
- **Task 9:** Stability analysis of time-varying partitioned large-scale systems with non-centralized MPC.

- **Task 10:** Proposal of a benchmark case of power systems with time-varying topologies.
- **Task 11:** Review of EGT-based DMPC.
- **Task 12:** Design of EGT-based DMPC for large-scale linear systems with disturbances.
- **Task 13:** Design of output-feedback EGT-based DMPC.
- **Task 14:** Development of event-driven partitioning methods for distributed control of large-scale systems with time-varying topologies.
- **Task 15:** Analysis of the interaction between time-varying partitioning and distributed control methods proposed in tasks 12 and 13.
- **Task 16:** Simulations that illustrate the performance of the closed-loop system controlled by the distributed control methods proposed in tasks 12-14.
- **Task 17:** Thesis report preparation.
- **Task 18:** Writing of a journal/conference paper that reports the last obtained results.
- **Task 19:** Report of the current progress in the regular INCITE workshops.
- **Task 20:** Academic/research stay with other national or international research groups.
- **Task 21:** Thesis defense.

Moreover, the timeline that shows the execution plan of the tasks is presented in Table 6.

Table 6: Working Plan

Tasks	2017				2018				2019			
	Jan-Mar	**Apr-Jun**	**Jul-Sep**	**Oct-Dec**	**Jan-Mar**	**Apr-Jun**	**Jul-Sep**	**Oct-Dec**	**Jan-Mar**	**Apr-Jun**	**Jul-Sep**	**Oct-Dec**
Task 1	■											
Task 2	■	■										
Task 3	■											
Task 4		■	■									
Task 5		■	■	■								
Task 6			■									
Task 7				■								
Task 8				■	■							
Task 9					■	■						
Task 10						■						
Task 11							■					
Task 12							■	■				
Task 13								■				
Task 14									■	■		
Task 15										■		
Task 16								■	■	■		
Task 17									■	■	■	
Task 18		■		■		■		■		■		■
Task 19		■		■		■		■		■		■
Task 20					■	■			■			
Task 21												■

5 Preliminary Results

Following the working plan, the literature review of non-centralized MPC methods, system partitioning, and dynamic optimal power flow problems has been carried out and is presented in Section 2. Furthermore, an approach towards online system partitioning has been proposed, as reported in [93][2]. Moreover, a study on the mitigation of communication failures on DMPC schemes has been carried out [94, 95].

5.1 Towards Online Partitioning of Large-Scale Complex System

In [93], time-varying large-scale flow-based systems are considered and a novel partitioning approach for such systems is proposed. Furthermore, a stability analysis for the closed-loop system controlled by a decentralized state-feedback control strategy is also provided. The stability analysis uses tools developed for switched systems and relies on the notion of dwell time, i.e., the time at which a system stays in one mode of operation.

The system considered is a flow-based network, the components of which are storages and controllable sources. It is described as a time-varying graph $\mathcal{G}(k) = (\mathcal{V}, \mathcal{E}(k))$, where $\mathcal{V}$ denotes the set of nodes (inputs and states) and $\mathcal{E}(k)$ denotes the set of edges that shows the relationship between the inputs and the states. Furthermore, the dynamics of the system are described by using a linear time-varying state-space model, as follows:

$$\boldsymbol{x}(k+1) = \boldsymbol{A}(k)\boldsymbol{x}(k) + \boldsymbol{B}(k)\boldsymbol{u}(k), \tag{1}$$

where $\boldsymbol{x}, \boldsymbol{u}$ denote the states and inputs of the whole system and $\boldsymbol{A}, \boldsymbol{B}$ denote the state-space matrices that are time-varying, i.e., $\boldsymbol{A}$ and $\boldsymbol{B}$ change at certain time instants.

The method consists in building a library of partitions that correspond to the time-varying system dynamics. Furthermore, when the $\boldsymbol{A}$ and $\boldsymbol{B}$ switch, the partition is also changed accordingly. Additionally, a multi-step partitioning algorithm is proposed to construct the library of partitions. The goal of the partitioning algorithm is to obtain p sub-systems that are non-overlapping, have minimum coupling, and have a balanced number of nodes (inputs and states). The algorithm consists of three steps:

1. coarsening, which reduces the size of the graph by merging anchor elements, i.e., elements that have an edge with only one input, to their corresponding input,
2. initial partitioning, the output of which is an unbalanced partition, and
3. refining, which is an iterative procedure that improves the solution at each iteration by moving one node from one sub-system to another and has a possibility to be implemented in a distributed fashion.

Once a partition is obtained, a stabilizing decentralized state-feedback gain is computed by solving a linear matrix inequality. Thus, the offline computations result in a library of partitions and that of state-feedback gains. However, due to the time-varying nature of the system, stability cannot be guaranteed just by implementing a state-feedback control strategy. One way to provide a stabilizing control strategy is by ensuring that each mode and the corresponding partition are active for, at least, a certain period of time, which is called the average dwell time. This result is shown in [93, Theorem 1].

A numerical study is also carried out. In this case study, a system that consists of 8 states, 12 inputs, and 4 pairs of A and B matrices, describing its dynamics, is considered. The matrices are built by a random function. In the simulations, each mode of the system is partitioned into three

[2] T. Pippia and W. Ananduta are both co-first authors.

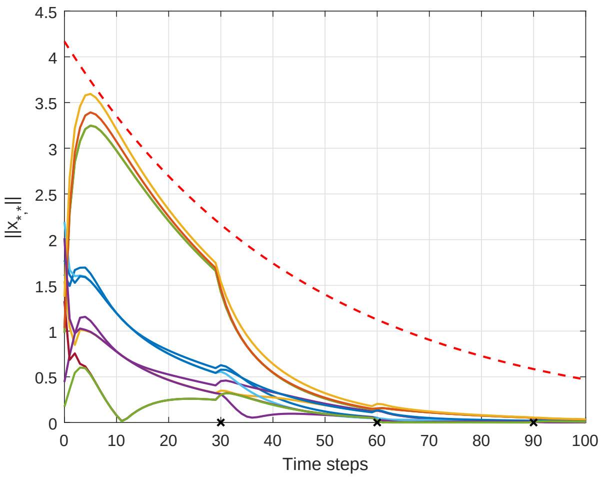

Figure 4: The evolution of the norms of states (solid lines) and the exponential upper bound (dashed line). The cross markers indicate the time instant at which the switch occurs.

sub-systems by the proposed approach. Furthermore, a decentralized state-feedback controller is designed. Additionally, the switching condition, related to the average dwell time, which in this case is 30s, is satisfied. Figure 4 shows the norms of the states, which illustrate the convergence of the states to the origin as the equilibrium point that has an exponential stability.

The partitioning approach proposed in this work can be considered as a step toward online partitioning methods, which are the topic of interest in this thesis. The library of partitions allow the system to switch from one partition to another when the $\boldsymbol{A}$ and $\boldsymbol{B}$ matrices switch. As future work, an online distributed partitioning method will be developed based on the current proposal.

5.2 Mitigation of Communication Failures in DMPC Schemes

The work presented in [94] and [95] discusses the problem faced by DMPC controllers when communication failures occur and proposes two information-exchange protocols as solutions to deal with this issue. Under some assumptions, these proposals not only improve the resilience of the controller against some communication failures but also relax some communication requirements of the controller. Furthermore, a case study of interconnected microgrids is used to illustrate the application of the proposed approaches to a DMPC scheme utilized to control the microgrids.

Information sharing is necessary for any DMPC strategy. In this regard, communication failures, i.e., broken communication links, could yield to suboptimality, even infeasibility. A discussion on the impact of communication failures to a DMPC strategy based on dual decomposition is presented as an example in [95]. Furthermore, different DMPC strategies require different communication structures. For instance, the cooperative DMPC method proposed in [63] requires that each sub-system to communicate with all other sub-systems while the non-cooperative DMPC method proposed in [61] requires that each sub-system to exchange information with neighbor sub-systems, i.e., those that influence the dynamics.

In order to deal with communication failures and relax the communication requirement of a DMPC strategy, [94] and [95] propose to apply consensus-based algorithms as an information-exchange protocol. The main requirement of the proposed protocols is the connectivity of the information-sharing network. This requirement is more relaxed than the standard communication requirement of DMPC strategies, which is previously explained. Furthermore, when some communication links fail, as long as the information-sharing network is still connected, the proposed protocols still work.

As an initial idea, the work in [94] proposes to apply the standard distributed consensus [96], i.e.,

$$\dot{\boldsymbol{p}}_{i,t} = \sum_{j \in \tilde{\mathcal{N}}_i} (\boldsymbol{p}_{j,t} - \boldsymbol{p}_{i,t}), \quad \forall i \in \mathcal{V}, \tag{2}$$

where $\boldsymbol{p}_{i,t} \in \mathbb{R}^{n_s}$ denotes the information state of sub-system i, $\mathcal{V}$ denotes the set of sub-systems that are involved in exchanging information, and $\tilde{\mathcal{N}}_i$ denotes the set of neighbors of sub-system i in the information-sharing network[3], i.e., the network through which the information is exchanged. In addition n_s denotes the size of all information that is exchanged in the network. Furthermore the information state of each sub-system is initialized as follows:

$$\begin{aligned} \boldsymbol{p}_{i,0} &= [\boldsymbol{p}_i^{j\top}]_{j\in\mathcal{V}}^\top \in \mathbb{R}^{n_s}, \quad \text{where} \\ \boldsymbol{p}_i^j &= \begin{cases} n\boldsymbol{s}_i & \text{if } j = i, \\ \boldsymbol{0}_{n_{s,j}} & \text{otherwise,} \end{cases} \end{aligned} \tag{3}$$

in which $\boldsymbol{p}_i^j \in \mathbb{R}^{n_{s,j}}$, for all $j \in \mathcal{V}$, are the elements of $\boldsymbol{p}_{i,t}$, $\boldsymbol{s}_j$ denotes the information that is shared from sub-system j, n denotes the number of sub-systems, and $n_{s,j}$, for all $j \in \mathcal{V}$, denotes the size of information that is shared from sub-system j. Note that $n_s = \sum_{j\in\mathcal{V}} n_{s,j}$. Based on the dynamics (2) and initialization procedure (3), the information states of all sub-system converge to $\boldsymbol{s} = [\boldsymbol{s}_i^\top]_{i\in\mathcal{V}}^\top$, as shown in [94].

In [95], a dynamic consensus algorithm[4] that is based on distributed projection dynamics (DPD) [6] is proposed as an information-exchange protocol. The dynamics of the protocol are as follows:

$$\boldsymbol{p}_{i,t} = \boldsymbol{q}_{i,t} + \boldsymbol{r}_i, \quad \forall i \in \mathcal{V}, \tag{4a}$$

$$\dot{\boldsymbol{q}}_{i,t} = \alpha \sum_{j\in\tilde{\mathcal{N}}_i} (\boldsymbol{q}_{j,t} + \boldsymbol{r}_j - \boldsymbol{q}_{i,t} - \boldsymbol{r}_i), \quad \forall i \in \mathcal{V}, \tag{4b}$$

where $\boldsymbol{p}_i, \boldsymbol{r}_i, \boldsymbol{q}_i \in \mathbb{R}^{n_{s,v}}$ are the information state, the reference, and the internal state of the i^{th} node, respectively, $\tilde{\mathcal{N}}_i$ is the set of nodes that are the neighbors of the i^{th} node in $\tilde{\mathcal{G}}_v$, i.e., $(i,j) \in \tilde{\mathcal{E}}_v$ for all $j \in \tilde{\mathcal{N}}_i$, and $\alpha \in \mathbb{R}_{>0}$ is the constant gain. Note that $n_{s,v}$ denotes the information of sub-system v that is exchanged between the sub-systems. Furthermore, the references of all nodes in $\mathcal{V}$ are given by

$$\boldsymbol{r}_i = \begin{cases} |\mathcal{V}|\boldsymbol{s}_v, & i = v, \\ \boldsymbol{0}_{n_{s,v}}, & \text{otherwise,} \end{cases} \tag{5}$$

where $\boldsymbol{s}_v$ denotes the information that is shared from sub-system v. Furthermore, the internal states are initialized as

$$\boldsymbol{q}_{i,0} = \boldsymbol{0}_{n_{s,v}}, \quad \forall i \in \mathcal{V}. \tag{6}$$

Following the dynamics (4) and the initialization of the references as in (5) and the internal states as in (6), the information states $\boldsymbol{p}_{i,t}$, $\forall i \in \mathcal{V}$ converge to $\boldsymbol{s}_v$.

Remark 1 *The size of the information states, $\boldsymbol{p}_{i,t}$ $\forall i \in \mathcal{V}$, defined in [95] are different than that in [94]. While in [94] the information from all sub-systems is considered, the description in [95], without loss of generality, only considers the exchange of information from one sub-system to the other sub-systems.*

The main difference between the standard consensus-based protocol, proposed in [94], and the DPD-based protocol, proposed in [95], is the initialization of the information states. The standard consensus-based protocol requires to re-initialize/reset the information states at every

[3]The topology of the information-sharing network might be different than that of the physical network, which describes the physical coupling among the sub-systems.

[4]Dynamic consensus tracks the average of time-varying references [97].

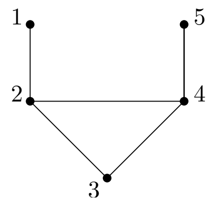

Figure 5: The topology of the graph. Circle marks represent the nodes and the solid lines represent the link between two nodes.

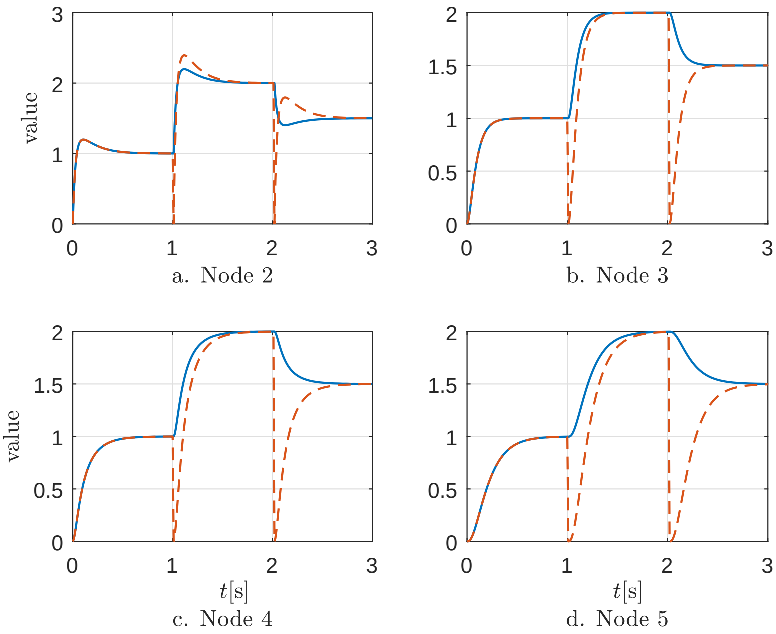

Figure 6: Comparison between the standard consensus-based protocol (dashed lines) and the DPD-based protocol (solid lines).

time the protocol is used. Differently, the DPD-based protocol only requires the initialization of $\boldsymbol{q}_{i,t}$ once. Instead, it only requires to update the reference, which depends on the information that is shared. The different performance of both protocols can be seen from the following numerical simulation.

Consider an undirected connected graph as shown in Figure 5. In this example, the 1st node has a scalar information that varies along the time and that is shared to the rest of the nodes, i.e.,

$$s_1 = \begin{cases} 1, & \text{for } 0 \leq t < 1, \\ 2, & \text{for } 1 \leq t < 2, \\ 1.5, & \text{for } 2 \leq t < 3. \end{cases} \tag{7}$$

This example is relevant with the application of the protocol to some iterative distributed MPC strategies, in which the neighboring sub-systems must exchange some information at each iteration. Figure 6 shows that the information states of nodes 2, 3, 4, and 5 converge to information source s_1 by using both protocols. Moreover, it can be seen that the DPD-based protocol has a shorter settling time than the standard consensus-based protocol, since the DPD-based protocol does not have to reset the internal states.

An economic dispatch problem for interconnected microgrids is used as a case study to show the advantages of the proposed protocols when they are applied to a DMPC strategy based on dual decomposition. Upon deriving the model of the system and stating the optimization problem, which is convex, the iterative DMPC algorithm is designed. Due to the convexity of the problem, the DMPC algorithm should be able to obtain the optimal solution. In this algorithm, it is required that neighboring sub-systems exchange information twice at each iteration. In the simulations, four scenarios are considered, which are

- **Scenario 1:** The DMPC algorithm with the default information-exchange protocol, i.e., direct communication between neigboring sub-systems, operates in the information-sharing network without failures.
- **Scenario 2:** The DMPC algorithm with the proposed information-exchange protocols, operates in the information-sharing network without failures.
- **Scenario 3:** The DMPC algorithm with the default information-exchange protocol operates in the information-sharing network with failures.
- **Scenario 4:** The DMPC algorithm with the proposed information-exchange protocols operates in the information-sharing network with failures.

The simulation results of Scenarios 1 and 2 show that the same optimal solutions are obtained when the DMPC algorithm applies either the default or the proposed protocol when there is no communication failure. Furthermore, the results of Scenario 3 shows that during communication failures the DMPC algorithm with the default protocol obtains a suboptimal solution (shown by the increase of cost, which in the simulation is $16\% - 18\%$). In contrast, the results of Scenario 4 show that the optimal solution can still be obtained when the proposed protocols are applied during failure. Note that during the communication failures, i.e., in Scenarios 3 and 4, the information-sharing networks are connected.

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