Review

Engineering Emergence: A Survey on Control in the World of Complex Networks

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Abstract: Complex networks make an enticing research topic that has been increasingly attracting researchers from control systems and various other domains over the last two decades. The aim of this paper was to survey the interest in control related to complex networks research over time since 2000 and to identify recent trends that may generate new research directions. The survey was performed for Web of Science, Scopus, and IEEEXplore publications related to complex networks. Based on our findings, we raised several questions and highlighted ongoing interests in the control of complex networks.

Keywords: complex networks; networked control; decentralized control; emergence; survey

1. Introduction

Network science [1] has become an important field of research in the last 20 years [2,3] and is the result of the convergence of many other research fields [4]. *Network science* is *"the study of the theoretical foundations of network structure/dynamic behavior and the application of networks to many subfields"* [4] (p. 5). The study of networks has roots in *graph theory* [5] since real-world networks can be mathematically represented by graphs [6,7].

Network science provides powerful methods that transform our understanding of *complex systems* [8]: *complex networks (CNs)* are a subset of *complex systems* [9], and many complex systems can be described using network structures [10]. *Complex networks* are systems that provide a universal language to understand patterns of interaction [7], organization, and network topology [11].

Complex systems consist of individual entities (subsystems), self-organize, are large scale, emergent, nonlinear, and heterogeneous, and have no single point of control [9,12,13]. *Complex systems* can be defined as systems *"in which there are non-trivial relationships between cause and effect: each effect may be due to multiple causes; each cause may contribute to multiple effects; causes and effects may be related as feedback loops, both positive and negative; and cause-effect chains are cyclic and highly entangled rather than linear and separable"* [14] (p. 14). Usually, *complex systems'* definitions emphasize the interconnections between (many) component subsystems, whether they focus on causality, nonlinearities, scale, resilience, or nestedness.

Complex networks are networks with nontrivial topological features [15,16]. Real-world complex networks are ubiquitous in our everyday lives [15] and share several common characteristics [17], such as small-world [18], scale-free [19], hierarchical structure [20], etc. Examples of real-world complex networks include the Internet, electric power grids, metabolic networks, supply chains, the world trade web, and urban road networks, among many others [21].

Emergence is an essential characteristic of complex systems [22] and a basic feature of complex networks [23], reflected in system-wide processes such as evolution, adaptation,

or self-organization [12]. *Strong emergence* is a holistic property of the complex system as a whole, irreducible to its component subsystems, whereas *weak emergence* is the predictable integration of intrinsic properties of the subsystems and their localized interactions [24]. *Emergence* can be defined as *"the phenomena that emerges (is not reduced) from nonlinear interactions among (large-scale) lower-lever inter-independent components and can be observed only in higher or system level"* [12] (p. 3577).

In the world of complexity, systems of systems (SoSs) [25] and complex networks are terminologically different, but in actuality, the difference between them is found in the way each of them reflects the concept of multi-resolution. SoSs focus on nestedness, while CNs on clusters, seemingly "flatter" in structure than SoSs [26]. In actuality, access to a CN cluster works the same as access to a nested component of an SoS: few paths into a smaller world of interconnected processes. The control issues of SoSs apply to CNs, revealing an ever-increasing need for specialized tools and frameworks. As such, control engineering faces challenges related to heterogeneity (pertaining to structure, information, and resource access, communication and interaction methodologies), remote monitoring and control, scalability, geographical distribution (in the case of large-scale systems), flexibility, and configurability [27].

The aim of this paper was to survey the interest in control related to complex networks research over time since 2000 and to identify recent notable contributions that may generate new research directions. To understand the evolution of research in the field of network science, we extracted the number of publications for each year since 2000 and until the present from the following digital libraries: Web of Science [28], Scopus [29], IEEEXplore [30], and ACM-DL [31]. We considered the following keywords as our survey was focused on emergence and complex network control contributions: *"Network Science"*, *"Complex Network"*, *"Complex Network Control"*, *"Networked Control"*, *"Decentralized Network Control"*, and *"Distributed Network Control"*. Table 1 and Figure 1 show comparative results. We noticed that for ACM-DL, the six keywords returned similar numbers and trends, indicating a possible overlap in the returned results, and so were deemed unsuitable for comparative analysis.

Although complex networks is one of the main topics of network science, we noticed that many authors do not use the word *complex* when referring to complex networks. As shown in Figure 1a–c, the number of papers using the "Network Science" keyword is higher than the number of papers using the "Complex Network" keyword. For instance, papers related to neural networks [32], wireless networks [33], supply chain networks [34], social networks [35], etc., used complex networks and graph theory concepts.

This survey is structured as follows: Section 2 presents contributions to the field of networked control systems. Section 3 present contributions to the control of complex networks. Section 4 discusses decentralized control in the context of complex networks. Section 5 presents open research questions and Section 6 the conclusions.
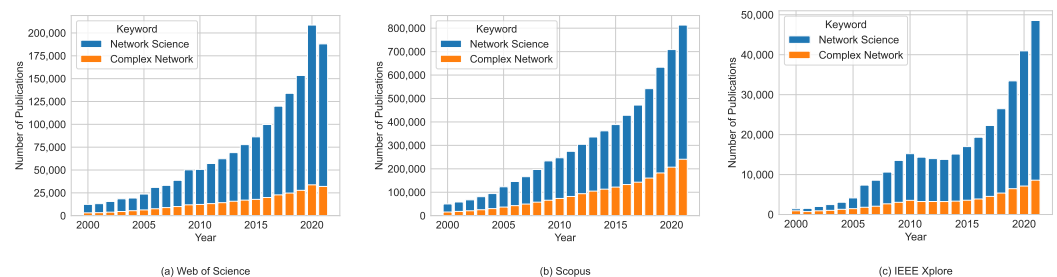

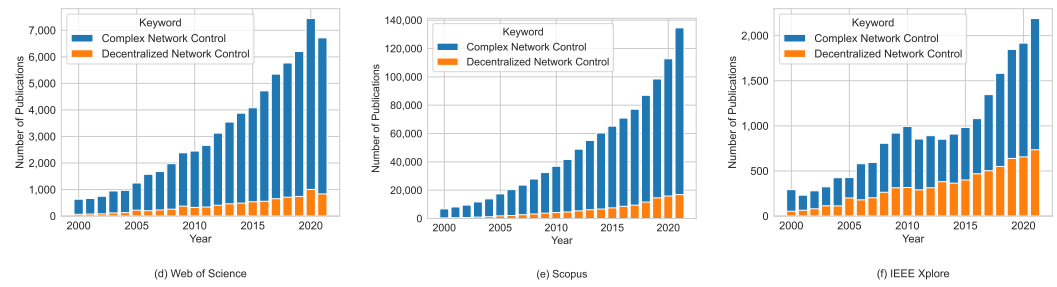(a) Web of Science   (b) Scopus   (c) IEEE Xplore

Figure 1. *Cont.*

Figure 1. Total number of "Network Science" related publications over time from 2000 to 2021.

Table 1. Network-Science-related publications on the Web of Science, Scopus, and IEEEXplore from 2000 to 2021.

Repository	Keyword	Query	Total Number of Publications
Web of Science	Network Science	ALL = (network science)	1,562,859
	Complex Network	ALL = (complex network)	316,545
	Complex Network Control	ALL = (complex network control)	68,768
	Networked Control	ALL = (networked control)	500,852
	Decentralized Network Control	ALL = (decentralized network control)	8846
	Distributed Network Control	ALL = (distributed network control)	62,227
Scopus	Network Science	ALL (network AND science)	6,729,160
	Complex Network	ALL (complex AND network)	2,019,945
	Complex Network Control	ALL (complex AND network AND control)	1,060,716
	Networked Control	ALL (networked AND control)	181,627
	Decentralized Network Control	ALL (decentralized AND network AND control)	129,084
	Distributed Network Control	ALL (distributed AND network AND control)	691,056
IEEEXplore	Network Science	("All Metadata": network science)	335,426
	Complex Network	("All Metadata": complex network)	72,199
	Complex Network Control	("All Metadata": complex network control)	20,326
	Networked Control	("All Metadata": networked control)	290,125
	Decentralized Network Control	("All Metadata": decentralized network control)	7209
	Distributed Network Control	("All Metadata": distributed network control)	50,630

2. Control vs. Networks

2.1. Control vs. Networks: Are We Speaking the Same Language?

The *control vs. networks* problem is a historical coin with two facets: (a) *control of the network* and (b) *control over the network* [36]. Despite intersecting characteristics, this disambiguation is necessary due to the intrinsically dichotomous nature as processes and as approaches to solving the control problems.

Control of the network revolves around the challenges posed by the communication network [36]. This field studies problems that deal with the network itself, which can lead the system to instability and low performance: data transmission, management and routing of data packages, connectivity and security, and communication delays.

Control over the network refers to distributed and decentralized control design based on a physical network [36]. This field deals with control problems within a network, seen as an interconnected and interacting set of subsystems, with issues related to network overload, available processing power, delays, and bandwidth.

In the world of control theory and applications, a hefty portion of current research is centered on the control of the network, rather than design methodologies for control systems structured as complex networks. If, for instance, a handful of cascaded loops are difficult to design, how does this translate to networks of hundreds or thousands of loops? Interestingly, the overlap between control of and over the network resides in delays. An indubitable source of closed-loop instability, delays generated by communication can affect the performance of a control system that uses said network. An improperly managed

communication medium impedes the achievement of control objectives, and as a result, these two fields have somewhat merged in applications.

A note on terminology: even though publications [37–39] often classify networked control systems in these two categories, *control of the network* would be more accurately referred to as *network control*, while *control over the network* would be *networked control*. The first one uses a noun, the second one an adjective, signifying a property rather than a type of process. In network science terms, the first category deals with the edges (the medium for information transmission), while the second one with the nodes (each local loop as a whole, i.e., the connected set of plant, sensor, controller, and actuator). In what follows, we use the acronym NCS to mean control *over* the network.

In the mid-to-late 2000s, along with the increase in computing power, *control of complex networks* emerged (Figure 1). The question now is: Where does it fit? Is it about connectivity, managing states, or something entirely different?

2.2. Control of the (Communication) Network

Communication networks are defined as (large) sets of interconnected nodes capable of receiving and transmitting information [40]. They predate the concept of control over the network [40], have been and still are well studied [41], tackled from the synchronization [42], load balancing (routing, scheduling) [43], and structural (topology) [44–49] perspectives, with implementations in wired (e.g., telephone, cable, computer) or wireless (e.g., mobile communication, sensors) forms. From the control angle, communication network challenges concern real-time performance, traffic management, and communication protocols. While the terminology might appear different, the underlying issues to be solved are the same.

Real-time operation of networks as the backbone of communication for control systems introduces performance requirements related to the *time* in which information is produced (by the control system components) and transmitted (by the network) and translates to time synchronization issues across the network [50], or more precisely, the phase and frequency synchronization of tick generators [40,51]. Recent surveys indicate an increasing interest toward wireless networks [52–56].

Traffic management aims for efficient communication without congestion. Load balancing solutions [40] look at both real-time traffic distribution throughout the network and at the computational resource distribution of the nodes, or resource allocation problems [57]. Oftentimes, the latter leads to sacrificing node performance for the sake of network optimization [58]. Recent surveys look at wireless networks [59] and redefining network architectures to manage big data loads, i.e., software-defined networks [60].

Communication protocols require compatibility across nodes, infrastructure, and transmission mediums and usually prescribe to ensuring real-time performance and traffic management requirements [61,62]. Security is an overarching issue with rapid-paced research as new loopholes are exposed [63–65].

2.3. Control over the Network

Over-the-network NCSs are control systems where the loop is closed through a real-time communication network (Figure 2). They exist outside the restrictions of the traditional point-to-point wired control structures [66]. The key advantage of NCSs is that the required information, no matter its type or purpose, is exchanged through a network between the loop components (sensors, controllers, actuators, etc.). Other benefits that put NCSs in the spotlight of the research community relate to the decentralization of control, resource sharing, remote operation, reduced wiring and simple installation, modularity, mobility, flexibility in introducing or removing components to and from the network, and the easy design of large-scale control systems [26,67,68].
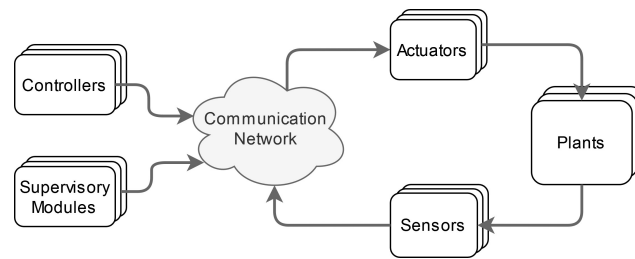
Figure 2. Networked control systems concept.

NCSs exist over a shared communication network and have remote control capabilities. The NCS design process aims to ensure quality of service (e.g., efficient transmission rates, minimal communication errors) and quality of control (loop performance) [69]. While performance requirements can be described for each control system, their placement in the network comes with a series of challenges [68]. Issues such as packet loss and synchronous communication are solved within the design communication network itself (i.e., the *control of the network* field). However, two types of network-introduced challenges affect the very performance of the control loops that are ultimately reflected in the controller computation: asynchronous behavior and time delays.

Asynchronous behavior in NCSs has two causes: data quantization generating different sampling times for the nodes and event-triggered methods. The latter appeared in response to the Zeno behavior, in which excessive redundant commands or sensor measurements are transmitted in between loop components, exercising unneeded strain on actuators and increasing network traffic unnecessarily [70]. A widely adopted solution against the Zeno behavior is known as event-triggered control [70–73], which functions based on the principle that information should be sent over the network only when an event (internal, for instance a change in operating point, or external, for instance a disturbance) has caused a marginally significant change in the variable to be transmitted. Both heterogeneous sampling times and event-triggered communication demand asynchronicity from the communication network, which, at first glance, might seem incongruous with the synchronization requirement. The solution arrived from real-time control [74–79], which, through effective combinations of deadlines and interruptions, allows for the asynchronous behavior of control systems to be compatible with the synchronous functioning of the communication network.

Time delays generated by the communication network affect the control loops as any other time delays, pushing them closer to instability regions [80]. They are caused by node processing (stalling task execution), queuing (waiting to access resources), transmission, and propagation (paths through multiple nodes) [81,82]. Moreover, these time delays can be constant, varying, random, and usually difficult, if not impossible, to estimate even though attempts are found throughout the literature [27,83–87]. Controller designs that account for network-induced delays are also widespread, ranging from formal robust and optimal control, to intelligent and heuristic approaches [88–95]. A recent survey [96] summarized time delay approaches to NCSs and how they fit with event-triggered and scheduling methods.

Issues of security and safety are also tackled in NCSs. Approaches based on control systems principles have been popular, ensuring network resilience against attacks [97–103], and complementing fault tolerance research [104–109].

A large amount of research on control systems has made use of the NCS's features and benefits in the past two decades, with the popularity of the field reflected in a plethora of surveys every few years that either discuss NCSs in overview or focus on particular issues [26,36–39,67,68,110–112]. Although it is not clear yet how the rise in complex networks affects general NCSs, we expect overlapping issues to make way for an increase in the diversity and ingenuity of control approaches and applications.

2.4. Predictive Control: A Deserving Hero

In NCSs, the need to integrate the management of time delays in the controller design [110,113] has been answered, among others [114], by predictive control approaches. In this survey, we focused on predictive control because it has the capacity to maintain control performance even for unknown and varying time delays. The main (and better-known) types of control systems with predictive properties are *model predictive control* (MPC) and *Smith predictors*. Where MPC has most often a discrete implementation, Smith predictors are usually continuous controllers, although the opposites exist. They are both based on a priori knowledge of the plant model and time delays, but display robustness to variance in time delay.

MPC controllers are inherently robust, offering optimal or suboptimal solutions with good performance even when disturbances are unknown [115] or uncertainties are significant [116]. Networked MPC considers various configurations: event-triggered [117], buffered [118], and nonlinear [119]. While specific surveys on networked MPC have eluded our searches, MPC techniques are included in NCS surveys [120,121], and the literature makes up for it in application diversity [122–131].

A properly tuned Smith predictor can maintain loop stability and performance for significant variations of time delay [132] or even for unknown or assumed plant dynamics [133]. Application to NCSs range from UAV network control [134], packet loss management [135], combinations with generalized predictive control [136] or fuzzy controllers [137], and others [138–141].

In light of these results, we have to wonder: Will predictive control be the instigator of merging requirements for both NCSs and communication networks? Moreover, since time delay management is performed at the node level in the predictive approach, it raises the question whether the future of the combined control *of* and *over* the network fields resides in complete decentralization for both.

3. Control of Complex Networks: Is Emergence Lost?

Complex networks consist of vertices (nodes) and edges (links) [17]. Information, energy, or matter is processed by the nodes and transmitted through the links. The manner in which these processes are understood and represented dictates the type of models, control, and purpose of control for complex networks.

Many natural complex systems are important to everyday life and can be modeled as networks [142]. Undesirable behavior in complex networks (e.g., epidemics [143], power outages [144], economic crises [145], abuse of dominant position [146]) have motivated the research in the field of complex network control [42,142].

The purpose of complex network control is to obtain a specified or desired behavior across the entire network. This can be achieved by driving or maintaining the network to/in a desired state. The very nature of complex systems means that there is no central authority; therefore, all control actions must originate from nodes toward other nodes. However, are design approaches respecting this decentralization of decision (bottom-up), or is the hand of the designer dictating overall patterns from a central control position (top-down), which is to ask: is emergence lost, or is it an inherent part of complex network control?

From the systems theory point of view, nodes are systems and links are the medium for transporting signals, which opens the playing field to dynamic modeling of complex networks as interconnected systems. Often, the formal approach to complex dynamics is centered on state-space representations [147], which can become very large in size [148] and have created interest in defining and managing the observability, controllability, and stability of complex networks. Matters of robustness follow. The information-theoretic perspective adds another set of measures in complex networks, related to entropy [149,150], which might open doors to controlling links and not only node states. This reminds us of the duality *control of* and *control over* the network, but in the case of complex systems, a clear classification is impossible because the dichotomy between *network as a whole* and

network as a bunch of nodes must not exclude the very essence of complexity, which is that *subsystem interactions matter* [151,152].

In the case of nonlinear state-space network models, the control problem shifts to approaches common to nonlinear dynamic systems in general, such as attractor basins for state-space trajectories of cyclic behaviors due to oscillation dynamics or due to cycles within the network (paths through nodes that reconnect with themselves). Here, the control problem looks at chaotic behavior and synchronization in complex networks. Ultimately, controlling node behavior means controlling node dynamics, which returns us to the same control purpose of managing node states or, better said, state transitions.

Controlling a network is not a trivial task, as a node can control at most one of its immediate neighbors if there are no cycles in the network [142] (as it happens, for instance, in global value chain networks [153]).

Complex network applications focused on network resilience explore the question: *How many nodes or links can be removed from the network before it fails?* As such, this is not a control problem, but an optimization of design issue. In the current literature, these applications fall under the scope of fault tolerance [154], often moving away from the characteristics that define complex networks. While structure-based control of complex networks might allude to resilience, its purpose is still that of managing network states (while extracting information from its structure), but not the structure itself [155].

Complex network control was explored by various researchers using traditional control theory concepts such as PID control [156], predictive control [157], optimal control [158], etc., but it appears that all these methods rely on the pinning control concept. This is because complex networks are defined by their topology and their nodes, and it is practically impossible to control a network without altering either the topology or the nodes. The pinning control problem deals with finding how many controllers are required and where to pin them in the network to effectively control the network [159].

Controlling each node in a complex network is expensive and practically impossible; thus, pinning control was introduced [159], and the minimum number of control points is correlated with the degree distribution of the network [142]. Pinning control is an effective strategy that takes into account both the topology and node dynamics [159], e.g., local linear feedback controllers are designed for nodes to control the network [160].

Many real-world scenarios require only a small fraction of nodes to be controlled [161], and in many cases, it is not feasible to control the full network [162]. Target control aims to control only a subset of network nodes instead of the full network [163], and this problem is equivalent to the maximum network flow problem [164].

3.1. Observability, Controllability, and Stability

A dynamical system is controllable if it can be driven from any initial state to a desired state within a finite time [165]. Kalman's controllability rank condition is the mathematical condition for controllability [165], but is computationally infeasible in the case of complex networks [166].

Structural controllability theory facilitates inferring the controllability of a network [167] as a function of its interconnection graph independent of the edge weights [168], providing a tool for directed networks [169]. The main focus of structural controllability is linear time-invariant systems, but network controllability can be analyzed using the Lyapunov-based technique in the case of nonlinearities and stochastic disturbances [42].

In large networks, it is often impractical to monitor the states of all nodes; therefore, determining if the network is observable is important [170]. A dynamical system is observable if the state of the system can be determined based on the input and measured output variables [171]. The condition for observability is a rank condition of the observability matrix, computationally unfeasible in the case of complex networks [42]. However, the number of sensors required to estimate the internal state of a complex system can be determined using the graphical approach [42].

The science of complex systems relies heavily on linear stability analysis [172]. Linear stability analysis essentially assesses the state of a dynamic system by examining the dominant curvature of the potential energy function near the state as per the Lyapunov exponents [172]. However, the linearization-based approach to stability is too local [42]; therefore, the basin stability approach [172] was proposed. Basin stability is a measure that is easy to apply, non-local, and nonlinear [42,172].

Robustness is the ability of networks to adapt to changes and can be measured using entropy methods [173,174]. Jiang et al. [174] proposed the uncertainty of node importance as a measure of robustness where node importance is determined by the node degree and betweenness centrality [174]. According to Safar et al. [173], the robustness of a complex network is correlated with its capability to handle internal feedback loops within the network.

Entropy in information theory is analogous to entropy in thermodynamics [175] and is related to the system's ability to possess new states and the system degree of chaos [173]. In complex networks, entropy may be used to analyze global value chain networks as it can provide information about import and export diversification [153], can help identify influential nodes [176], or can predict human mobility as it can determine the degree of predictability of a time series [177].

3.2. Synchronization in Complex Networks

Synchronization is an important topic for complex networks and has been observed in natural networks from various fields such as cell biology [178], neuroscience [179], etc. Certain networks require synchronization, for example power grids require synchronization to achieve a steady state [42], and for this reason, synchronization attracted much interest in complex network research.

Chaos theory has roots in nonlinear dynamic systems [180]. When there is simultaneous and positive and negative feedback, a system is in a chaotic state [181]. The bifurcation phenomenon emerges in dense networks [182], and this was observed in both random and scale-free networks [183]. For example, Liu and Chen [184] showed that a double-scrolling attractor emerged in an undirected network with eight nodes.

In 1990, Pecora and Carroll [185] discovered that two identical chaotic systems can be synchronized by coupling them with a common signal. Since then, chaos control and synchronization have received a great deal of attention [186] as synchronization can be used to explain natural phenomena, secure communications, image processing, etc. [184].

In many complex network models, stochastic uncertainty influences the system dynamics through sensor and actuation unreliability, communication failure, coupling uncertainty, or model inaccuracy [187], and this may lead to synchronization challenges. Lu and Chen [188] noted that synchronization can be chaotic or non-chaotic and proposed network synchronization criteria based on the Jacobian matrix for time-varying and time-invariant networks.

Network synchronization can be analyzed using criteria based on the Lyapunov and master stability functions [189]. Mai et al. showed [190] that chaos can be quenched by deriving stability conditions for the system using Lyapunov stability theory. However, is the emergence lost if the chaos is quenched by means of pinning control and synchronization? Is chaotic behavior the only emergent pattern of complex networks?

3.3. Emergence

According to De Wolf and Holvoet [191], there are four schools of research that regard emergence from different perspectives: (1) complex adaptive systems theory, (2) the synergetics school, (3) nonlinear dynamical systems theory and chaos theory, and (4) far-from-equilibrium thermodynamics. In complex adaptive systems theory, emergence results from interacting agents as macro-level patterns [192], while the synergetics school regards emergence as a macro-level coherent phenomenon influenced by an order parameter [191,193]. The central concept of attractors in chaos theory is an emergent behavior that

occurs naturally in many types of systems [194,195]. Under far-from-equilibrium conditions, a thermodynamic system can transition to spontaneous organization, a dissipative structure [196].

Emergence can be engineered [197]; therefore, it is not necessarily lost when the system is controlled, but certain emergent patterns such as chaotic behavior can be quenched [190]. According to Mittal and Rainey [198], emergence is positive if it maintains the component subsystems operational and fulfills the purpose of the SoS or complex system as a whole and negative when it leads to cascaded failures, load hot-swapping, etc.

The question now is: How exactly can we engineer emergence? Does control theory hold the key? Would a properly designed control system be able to maintain the resilience of emergent patterns and even guide the switch to other, desired patterns?

4. Engineering Emergence: Decentralized Control over Complex Networks

4.1. Distributed vs. Decentralized Control

The second disambiguation of this paper pertains to decentralized vs. distributed control systems as major structural players in control architectures. In what follows, we do not use the acronym "DCS" for either to avoid confusion. Figure 3 illustrates the centralized, distributed (hierarchical), and decentralized structures.
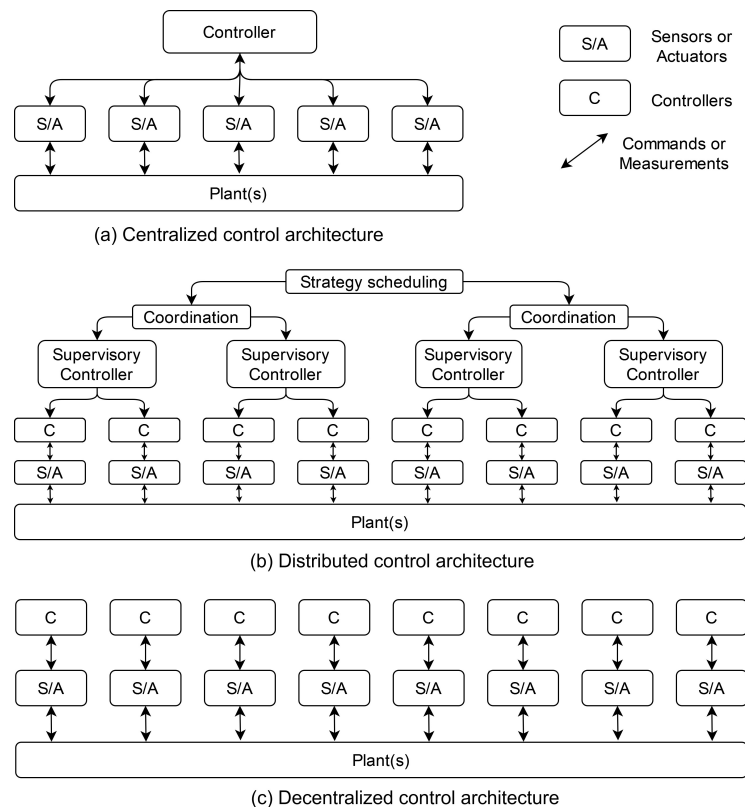

Figure 3. Control architectures.

Centralized control architectures pertain to structures in which commands are computed by one "central" entity, which is designated as the controller of the system [199]. All sensor information is received by the controller, and all commands are transmitted by the controller. The functioning and task execution of the entire system are dependent on the controller, and so, centralized architectures are not reliable in large networks due to load, traffic, and resource issues.

Distributed control architectures have hierarchical structures [200] supported by a control level in which local commands are computed at the location of the plant. On the next level, supervisory modules assign tasks to the controllers (i.e., change operating points or modes).

Further up the hierarchy are two coordination levels that deal with the high-level goals and objectives of the control system. Distributed control systems have been a staple of the manufacturing world [201]. While the plant-level control is not centralized, there is still a guiding action originating from a central entity.

Decentralized control architectures rely exclusively on local node control. Each control subsystem is only sensitive to and reacts to local events (i.e., within a predetermined vicinity of itself) [202,203]. Through the interaction of these components, desired global patterns are obtained. There is no entity *inside the system* with an overview of the whole system; at most an observer exists, external to the system, to recognize patterns. The decentralized approach is suitable for systems that can be decomposed, are geographically distributed, or exchange large quantities of data [204]. The design and behavior of decentralized systems are bottom-up processes.

Terminology problems arise when "decentralized" and "distributed" are used interchangeably [205], which often happens in the field of multi-agent systems (MASs). Although in MASs, these terms describe the behavior of the group as a result of the local interaction of agents (i.e., emergent behavior), they are not necessarily related to the control system. However, through a strange conjecture, a significant amount of advances in *decentralized control* have been made under the umbrella of MASs as swarms, robot groups, and other multi-agent applications tackled by control designers. We now have research in industrial automation (manufacturing) and MASs using the same word "distributed" to mean different concepts. Therefore, where do we draw the line, or better yet, *should* we draw a line? It is our opinion that perhaps the moment for a widely accepted set of unambiguous definitions has passed; what we can do, moving forward, is to keep this unintended diffusion of meaning in mind and apply it appropriately to each paper based on the context of the research.

4.2. Emergence and Consensus through Decentralized Control in Complex Networks

Extrapolating from the MAS concepts, we can define the problem of *decentralized control over a complex network* as an objective optimization problem [206] to be solved by the nodes of the network. Depending on how the optimization problem is posed, network behavior can be analyzed from the points of view of cooperation and coordination. Cooperation requires nodes to work together toward the achievement of their individual or common goals, while coordination refers to managing interdependencies (e.g., shared resource access). In *cooperative control*, while the objective of the network is global, the nodes solve the optimization problem locally and display a high level of interaction [207]. In *non-cooperative control*, nodes work toward their own, independent objectives [208]. The mechanisms for node interactions are either explicit—negotiation, consensus—or non-explicit—structured or emergent. Both cooperative and non-cooperative schemes fit into the decentralized structure if no supervisory type of entities exist in the network, which brings *consensus* and *emergence* to our attention in this survey.

Consensus refers to nodes that, while only having access to local knowledge or measurements, reach an agreement regarding a piece of information or state. The latter is of particular interest in control, as consensus mechanisms can guide the state of the network from one operating point to another [209]. Approaches to consensus are plentiful in the control world [210–213], although not many deal with complex networks specifically. A recent review [214] on consensus shed light on applications such as rendezvous, formation control, or wireless sensor networks.

In complex networks, consensus approaches are applied to clustering, connectivity, or network dynamics: managing stochastic fluctuations [215], robustness based on connectivity [216], positive edge constraints [217], behavioral consensus in evolutionary dynamics [218], observer-type protocols [219], nonlinear dynamics [220], three-body interactions [221], heterogeneous timescales [222], etc. When consensus requires that nodes in a complex network agree on aligning one of their internal states or parameters, temporarily or not, it becomes a case of *synchronization* (Section 3.2).

Emergence leads to patterns in the complex network, related to node location, degree, states, observable outputs, etc. While not necessarily resulting in synchronization, emergent behavior can produce agreements among the network nodes. From the control perspective, emergence becomes a problem of self-organization. In complex adaptive systems, for instance, nodes adapt (i.e., self-govern) to information exchanges and interactions with neighbors in their vicinity. However, whichever complex network behavior we look at, the matter of self-organization and thus emergence is a *local control problem within a decentralized structure*.

Research into self-organization is plentiful, especially in MASs [223,224]. In complex networks, self-organization is often regarded as a modeling problem [225–228]. The fact that deterministic models can be developed for microscopic dynamics [229] keeps these results relevant, even though control design has not yet been applied to all complex network types of self-organization models.

Thus, it is our opinion that emergence can be engineered (i.e., patterns at the network level can governed) through the objectives and design of local node controllers.

The simplest node control is open loop, known as reactive control in mobile robotics and MASs, in which nodes react to inputs without the presence of a feedback loop. One of the most famous applications for reactive laws is Boids [230], but newer applications have moved to local feedback in inventive configurations [231–234]. These results are fairly recent and not always explicit as concerns the design of local controllers.

Looking at node dynamics, the possibilities of control are indubitably as many as there are controller types out there in the control field, e.g., [235]; in this survey, we looked at predictive control as a connecting point between NCSs and decentralized control of complex networks. In decentralized schemes, local MPC controllers [236] are applied to energy networks [237], traffic [238,239], economic models [240], water management [241,242], supply chains [243], etc. Not all papers dealing with MPC's decentralized solutions mention complex networks explicitly, but the application processes are usually complex in nature (e.g., traffic networks).

We close with our own example of nested emergence engineered through self-organization: eSCAPE is a scalable control architecture for urban areas that supports bottom-up design in SoSs. In eSCAPE, emergence is reflected by its capacity to generate ad hoc on-demand control loops [244]. The nestedness of eSCAPE comes from the self-organization of agents (representing controllers, actuators, sensors, and nuclei with specialized communication units) in minimal cells (i.e., local control loops) and, if needed, in extended cells (in which the roles for acting and sensing might be taken by other cells). The architecture supports various mechanisms, such as negotiation [245] and decentralized control [204].

5. Open Questions and Perspectives

Network science and complex networks have become an increasingly popular research topic over the last 20 years. Although considerable progress has been made so far, there are still questions that are left unanswered. Throughout the paper, we raised a few questions that we highlight in this section.

The first question we raised (Section 2.1) refers to the place of complex network control under the wider umbrella of network-related control systems. Complex network research has been motivated by a deep need to understand the interconnected world in which biological systems (human or others), urban infrastructures, and developing technology come together to create new complex structures, from energy distribution networks to social media platforms that foster information exchange. Network science has a wide range of applications, and complex topological features arise in all types of networks, allowing the same complex network analysis tools to be used to extract information about networks from various fields.

Control of complex networks is rooted in established control practices, but at the same time reveals itself to be a stand-alone field, due to the infusion of ideas coming from understanding complexity in innovative ways. At the time of writing this paper, it is our

belief that only creativity is the limit as concerns the future of complex network control, with the caveat that we expect furthering of efficient resource utilization and sustainability in real-world applications.

In Section 2.4, we launched the hypothesis that predictive control will be the instigator of merging requirements for both NCSs and communication networks. In classical control theory, the predictive control approach enables the control of systems by managing time delays through the controller design. We estimate that predictive approaches will undoubtedly spread toward complex network control in bottom-up design strategies.

Emergent behavior in nature is ubiquitous. In complex systems at large, emergence is an important and defining characteristic. In Sections 3.2 and 3.3, we raised questions related to the nature and place of emergence in complex network control. Thus, we ask: Can we create artificial emergence? Is it possible to drive emergence through design, or is it a phenomenon spawning out of nowhere, only to slip through our engineering fingers as sand? The answer resides in decentralized control.

In complex systems modeling, the generative experiment [246] brought forth two bottom-up strategies for obtaining and analyzing emergent patterns: the predicting approach in which local node interactions are known, but not the overall emergent pattern, which can be observed under various created conditions, and the evolving approach in which patterns are "grown" out of local interactions with which the designer can experiment to obtain a desired global effect. We already see the former in chaotic systems approaches, and we see the latter compatible with decentralized control. Thus, we believe the answer to engineering emergence to be found in enhancing node agency through control capabilities.

Finally, we ask: Is there a metric for emergence or a metric that helps us classify emergence for all complex networks? If various distinct emergent patterns are observed in complex networks, based on node level interactions and the behavior of the whole network, what quantitative and qualitative conclusions can be drawn? Engineering emergence is a research ground in its infancy when it comes to control, but it shows great potential for new and exciting directions in control systems design.

6. Conclusions

In this paper, we performed a survey on complex networks in an attempt to identify potential research directions and unsolved problems related to control and emergence. We found that a considerable amount of progress was made in the field of complex networks since 2000 and the total number of contributions increased every year. The research field of complex networks is broad and multidisciplinary, so we focused our search on complex network control and the emergent behavior of complex networks. Network control can be regarded from three different perspectives we covered in this survey: control of the network, control over the network, and control of complex networks. We found interesting approaches to these problems, and we raised several questions throughout the paper. Although complex network control has received much attention over the last few years, network science is a field in full development and is currently better suited to represent our current interconnected world.

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