IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received March 6, 2020, accepted May 1, 2020, date of publication May 8, 2020, date of current version May 22, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2993527

Complex Systems: A Communication Networks Perspective Towards 6G

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ABSTRACT Over the last few years, the analysis and modeling of networks as well as the analysis and modeling of networked dynamical systems, has attracted considerable interdisciplinary interest, especially using the complex systems theory. These efforts are driven by the fact that systems, as diverse as genetic networks or the Internet can be effectively described as complex networks. Contrary, despite the unprecedented evolution of technology, basic issues and fundamental principles related to the structural and evolutionary properties of communication networks still remain largely unaddressed. The situation is even more complicated when we attempt to model the mobile communication networks and especially the 5th generation (5G) and eventually the forthcoming 6th generation (6G). In this work, we attempt to review basic models of complex networks from a communication networks perspective, focusing on their structural and evolutionary properties. Based on this review we aim to reveal the models of complex networks, that may apply when modeling the 5G and 6G mobile communication networks. Furthermore, we expect to encourage the collaboration between complex systems and networking theorists toward meeting the challenging demands of 5G networks and beyond.

INDEX TERMS Complex systems, complex networks, networked complex system, 5G, 6G, wireless communications, wireless networks, mobile communication networks, modeling.

I. INTRODUCTION

It is becoming apparent that many aspects of our environment can be viewed as a networked world. From the communication networks themselves (Internet, wireless networks, mobile networks, etc.) to the global ecosystem, from the road traffic network to the stock markets, from biological to social systems, massively interconnected and interacting components make up relatively vital systems in this world. These systems can be classified as complex systems.

Complex systems analysis can be considered as the science that studies how the elements of a system develop its collective behaviors, and how the system interacts with its environment. Qualitatively, to understand the behavior of a complex system we must initially understand not only the behavior of its constituent elements but also how they act together, to dictate the behavior of the entire system.

The associate editor coordinating the review of this manuscript and approving it for publication was Robert Hunjet.

Complex systems and their desired behavior, frequently involve references to emergence, adaptability, self-organization and evolution, resilience, robustness, decentralization, flexibility, and speed. Recently, literature focuses on the structural characteristics of complex systems which in this context can be characterized as decentralized, non-hierarchical, flat, amorphous, dispersed, and distributed ‘‘networks’’.

Complex systems, as networks of interacting entities are studied empirically, with the assistance of the rapid increase of available data of many different domains. Concurrently, these different domains appear to share several new and fundamental theoretical questions. This progress has encouraged the interdisciplinary development of the new science of complex systems which now becomes a well established scientific field.

The study of complex systems is about understanding indirect effects. Problems that are difficult to solve are often hard to understand because the causes and effects are not obviously related to an observer. Towards this direction, complexity theory studies how patterns emerge through the interaction of many interacting elements. In this space, emergent patterns can be perceived but can hardly be, if at all, predicted. Patterns may indeed repeat for a time, but we cannot be sure that they will continue to repeat, because the underlying sources of the patterns are not open to inspection (and observation of the system may itself disrupt the patterns) [1].

Newman [2], state that there are three interrelated approaches to the study of networked complex systems. These are: (a) find statistical properties, such as path length and degree distribution that characterize the structure and dynamic behavior of networked systems, (b) build models of networks that explain and help understand how they are created and how they evolve, and (c) predict the behavior of networked systems based on the measured statistical properties of the structure and the local properties of given vertices (study pattern formation and evolution).

Nowadays, systems become increasingly larger acquiring even more components, while the information flow in the system increases at a fast pace. Mobile communication networks and especially the 5G and the forthcoming 6G, are typical examples of systems that expand rapidly. Mastering their complexity (the high level of interdependence between their, often, very heterogeneous components), becomes a major hurdle, threatening to disrupt the information revolution. Designing, controlling, modeling and monitoring the behavior of such systems are the fundamental challenges that should be addressed. We need new paradigms as we are rapidly moving from systems based on closed hierarchical or semi-hierarchical structures to open and distributed, networked systems.

From a communication networks perspective, the key challenge is to learn how to design such networks that can self-organize, self-adapt and optimize their interactions and functions, in a continuous and robust manner to satisfy user demand. Fundamentally, the complex systems field can provide models, theories, mechanisms and approaches that allow for a principled design method to be developed, to address this key challenge.

Mobile communications networks and especially the forthcoming 5G networks, as well as the future 6G networks, are getting more complicated and heterogeneous. The typical operation of these networks with denser deployments, more base stations, countless users, as well as the new technologies that are expected to be introduced in 6G networks like the Artificial Intelligence (AI), Machine Learning (ML), Terahertz (THz) band communications, etc renders any known information theory incapable to directly model the behavior and their dynamics. This is further exacerbated, by the trend toward the softwarisation of networking functionalities and the dynamic orchestration of networked services [3]. Complex systems theory could become a useful and effective tool capable to model at some degree the behaviour of these networks.

In this paper we present complex systems from a communication networks perspective, revealing the issues and challenges as well as the way forward, towards 6G mobile communication networks. This work complements and extends the Technical Report TR-07-01 [4], with a focus on 5G/6G communication networks. Whilst the main focus of the study is 6G, most of the discussion is directly relevant to the evolving 5G.

The rest of the paper is organized as follow: In Section II, we briefly present some of the new challenges that are expected to be introduced in 5G/6G Wireless Communication Networks. In Section III we present the basic concepts of complex networks that are foreseen to appear in 6G. In Section IV we present the Complex Adaptive Systems (CAS) Properties while in Section V we present specific network modeling paradigms. In Section VI we introduce the mobile communication networks as complex systems and finally in Section VII a proposed way of modeling the 6G networks. Finally, in Section VIII we present our conclusions.

II. NEW CHALLENGES INTRODUCED IN 6G MOBILE COMMUNICATION NETWORKS

During the last two decades the cellular networks technology evolved from the 1st generation networks (1G) to the fifth generation (5G). 5G mobile communications networks are expected to be launched during 2020, while the research community has already started thinking how the next generation of wireless communication networks will be. A number of papers have been already published and in principle the authors agree that the 6G networks will introduce new technologies as well as revolutionary network characteristics [3], [5], [6].

The 5G has already introduced a number of novel ideas to meet the stringent requirements set out, as for example, heterogeneity, ultra dense cells, mm-wave, etc [7], [8]. Beyond that, the softwarisation of networking functionalities is widely socialized, as for example the Cloud- Native architecture [5]. This architecture is based on a data center in which all functions and service applications are running on the cloud data center. The cloud- native end-to-end network architecture, provides logically independent network slicing on a single network infrastructure to meet diversified service requirements and provides data center based cloud architecture to support various application scenarios.

Furthermore, new ideas are flourishing for the forthcoming 6G; for example the revolutionary concept that is being promoted for 6G networks and if adopted, is expected to change the whole perspective of mobile communication networks is the transformation from the ''connected things'' or Internet of Things (IoT) or Internet from Everything to the ''connected intelligence'' [9]. The ''connected intelligence'' with Artificial Intelligence (AI) and Machine Learning (ML) technologies, imposes much more stringent performance requirements, which inevitably will change fundamental network concepts and will increase the complexity of the network. To achieve ''connected intelligence'' very high and reliable data rates are required (approximately 1 Tb/s in many cases [10], [11] or 100 Gb/s individual data rate according to [6],

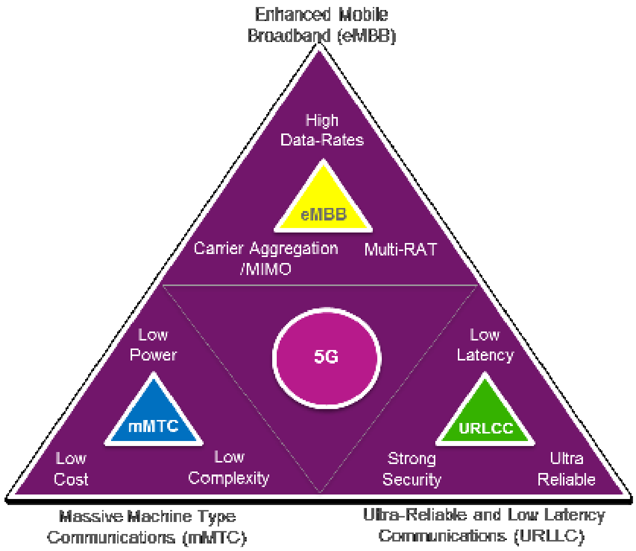


FIGURE 1. 5G service types [13].

as well as extremely low end-to-end latency, very high energy efficiency, efficient cloud applications (offering network as a service concept) and different and very broad frequency bands (up to THz range). Further to this, the integration and connection of terrestrial wireless systems with other systems, such as satellite and networked cars, networked UAVs, etc. will further increase the complexity of 6G systems.

According to the ITU [12] the 5G networks will support three heterogeneous service type that will definitely become the base for the 6G systems. These are the eMBB (enhanced Mobile Broadband), URLLC (Ultra Reliable Low Latency Communications) and mMTC (massive Machine Type Communications) (Fig. 1).

The purpose of eMBB service is to support very high peak data rates when the connections are stable, as well as moderate rates for cell-edge users. The mMTC supports very big number of devices which are active on demand or periodically (e.g. IoTs or Wireless Sensor Nodes that transmit small amount of data). The purpose of URLLC is to enhance the reliability of 5G networks by supporting transmissions of small amount of data that require very low latency and very high reliability from a specific number of devices. According to [9] 6G will support, beyond these services, another three advanced services. The Computation Oriented Communications (COC), the Contextually Agile eMBB Communications (CAeC) and the Event Defined uRLLC (EDuRLLC).

Computation Oriented Communications (COC) will render the devices capable to achieve a targeted computational accuracy based on the availability of the communications resources instead of the classical QoS methods that apply in traditional networks, including 5G. The Contextually Agile eMBB Communications (CAeC) will render the eMBB service provided in 5G networks more adaptive to the content of network including the network performance indexes like congestion, reliability, topology, location etc. The Event Defined uRLLC (EDuRLLC) service, as opposed to the 5G functionality, in 6G networks will have to support uRLLC in extreme and emergency events with variable traffic patterns, device densities etc. The complication is increased if we count that 6G technologies are expected to transform the world into a fully connected network that will turn several concepts into reality. Autonomous driving, Internet of Vehicles, space-air-ground integrated networks [14], virtual and augmented reality, fully connected and controlled Unmanned Air Vehicles (UAVs) [15], multi-way virtual meeting, virtual augmented reality (VAR) based gaming and remote surgery and holographic projection, will be some of these applications.

A. NEW NETWORK CONCEPTS THAT ADD TO COMPLEXITY

New network concepts that add to the complexity of the system are expected to be developed in 6G networks. Below the most important are presented.

1) DYNAMIC TOPOLOGY

The topology in 6G is expected to be completely dynamic. The fact that each user through its device or the plethora of smart devices that will form the IoT networks will be connected dynamically to the network that provides the best quality of service at the present moment, will drastically change the network dynamics. Autonomous driving Vehicles, Unmmaned Air Vehicles (UAVs), drones, satellite and radar communication, as well as the fact the many of these devices will be fast moving nodes will also add to the complexity. The need to correctly model the interference dynamics so that the nodes can quickly handover to the sub-network that provides the best quality will inevitably lead to the need for new mathematics and complex analysis models.

2) THz FREQUENCIES

The requirements for higher data rates and high spectral and energy efficiency (SEE) imposes the exploitation of frequencies beyond mmWave, at the terahertz (THz) band. This will lead to the development of ‘‘tiny cells’’ whose radius is only a few meters. These ‘‘tiny cells’’ will drive towards much denser deployments. Denser deployments will inevitably force the researchers to think of new traffic management techniques, new mobility management, congestion control algorithms etc. The very high THz path loss, the high sensitivity, high power and low noise will lead to a better understanding of physical layer properties and this understanding to the development of new MAC, link-layer and network protocols capitalizing on programmable e-m wave control [16], [17], to cope with the varying and unstable behaviour of the mmWave and THz environments.

3) ACCESS NETWORK FOR BACKHAUL TRAFFIC

According to the ITU focus group, the technologies for networks, 2030 (FG NET-2030) will require a huge increase in data growth which may render the access networks for Backhaul incapable to cope with it, as well as with the other quality requirement of the 6G technology. According to [6] measures to enhance research at higher bands like D-Band where the 60GHz spectrum is available will be embodied. More exotic, as for example, free space optical communications and quantum communications could also be consirered for 6G backhaul to meet the requirements. On the other hand in [18] the authors suggest to employ drones to complement terrestrial networks by providing connectivity to hotspots and to areas with scarce infrastructure. Drones and terrestrial base stations may require satellite connectivity with low orbit satellites (LEO) and CubeSats, to provide backhaul support and to increase wide area coverage. As we have already stated above, and as it is presented in [19] and [20] the integration of terrestrial, airborne, and satellite networks into a single wireless system will be essential for 6G. The Drones technology may lead to **cell-free** or UAV wireless networks or dronecells as described in [6]. All in all, the access networks for Backhaul is expected to be highly dynamic.

4) ARTIFICIAL INTELLIGENCE (AI) AND MACHINE LEARNING (ML)

Due to the complexity of 6G networks, it is expected that AI will be a key factor, critical for the successful and efficient operation of these networks. AI has already been used in wireless communications in every layer of the OSI stack. For example, in the physical layer for channel precoding, in network layer for traffic control, for fault prediction, authentication etc [9]. Regarding 6G networks, AI is expected to facilitate their operation since it is expected to leverage their complexity. The vast heterogeneity between the applications, the users and the supporting infrastructure render impossible to achieve any guaranteed performance without AI (Fig.2). The potential Terahertz or mmWave channels add to the complexity and non-linearity and add to the difficulty of modeling the wireless channels. A pervasive introduction of artificial intelligence at the edge of the network is expected to play a key role in aspects like semantic communication, machine learning and deep neural networks as well as to the holistic management of communication, computation, caching and control (C4) resources [3].

5) NETWORK FUNCTIONS VIRTUALIZATION (NFV) AND SOFTWARE DEFINED NETWORKING (SDN)

NFV and SDN are two functions that depend on virtualization. The purpose of these functions is to enable network design and infrastructure in software and then implementation by the underlying software across generic hardware platforms and devices. In principle, the SDN focus in separating network control functions from network forwarding functions, while NFV to remove network forwarding and other networking functions from the hardware on which it runs [21], leading to the softwarisation of networking functions. Network services orchestration, which is the execution of the operational and functional processes involved in designing, creating, and delivering an end-to-end service, add another layer of complexity. Artificial Intelligence, and

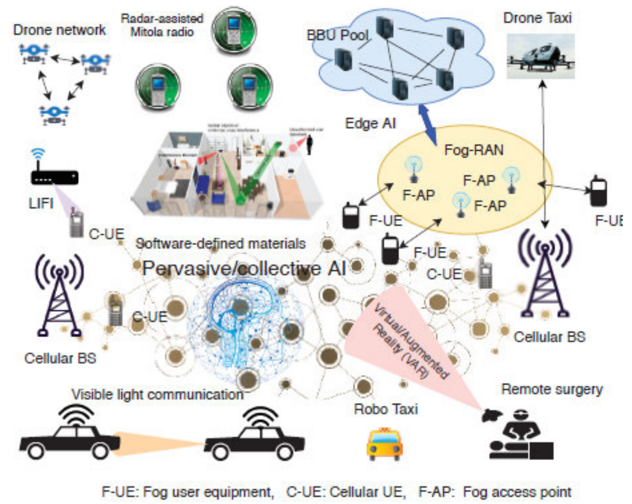


FIGURE 2. Artificial intelligence in 6G [6].

Machine Learning, SDN, NFV will enhance adaptivity in 6G networks and as a result complex dynamical systems theory will be relevant.

6) BLOCKCHAIN

Blockchain is also a technology that is expected to flourish in 6G networks, since it is considered a technology that can significantly contribute to the management of the massive data that are expected to be created and handled in 6G communication networks. The blockchain is managed by peer-to-peer networks and it can exist without being managed by a centralized authority or a server. Blockchain technology is expected to provide several facilities, such as interoperability across devices, traceability of massive data, autonomic interactions of different IoT systems, and reliability for the massive connectivity of 6G communication systems [22]. Blockchain traffic obeys to small world models and power laws as analyzed below.

7) MOVING NETWORKS

As technology evolves, the number of users that will demand high quality Internet services whilst being on a moving vehicle/train/plane etc is massively increasing. These users demand the same level of service as the static infrastructure users and 6G networks should be able to provide it. To address these concerns the concept of Moving Networks has been introduced [23]. Moving networks are a special category of ad- hoc networks where nodes move. Mobile nodes and Mobile Relay Nodes that typically use mobile small cells have already been proposed (e.g. see [23], [24]), to facilitate the provision of high speed internet to the "moving" users.

Moving networks, due to their highly volatile nature, experience significant quality issues since Vehicular Penetration Loss (VPL) can be observed due to the velocity of the vehicles and the attenuation of the radio signals that travel from the base station (BS) to the users devices, inside the vehicles or even to the vehicles themselves. This fact, inevitably, leads to increased interference and poor performance [25]. Moving devices may suffer from low signal quality caused by the poor macro antenna coverage of base stations inside vehicles with metallic walls. According to [25], in such cases, the Vehicular Penetration Loss (VPL) can be as high as 25 dB in a minivan at the frequency of 2.4 GHz, with higher VPLs expected in higher frequency bands as well as in well insulated, metal high speed transportation means (trains, small airplanes etc). The problem is expected to intensify, when future mobile communication networks commence their operation in higher communication frequencies.

An effective solution to VPL could be network densification. Although, denser deployments lead to higher inter- cell interference, an advantage of Mobile Nodes (MNs) is that, compared to regular user equipment (UE) devices, the MNs are less constrained by power and transceiver complexity [26]. Therefore, advanced algorithms, sophisticated multi-antenna solutions and more advanced signal processing techniques can be integrated into Mobile Relay Nodes (MRNs) to cancel interference [27]. According to [25] significant performance improvements were shown in both urban and rural scenarios, considering a ground moving vehicle. Furthermore, to meet the increasing bandwidth demands [25] proposes to adopt mm-wave technology in the Moving Networks, which will however exacerbate above stated losses.

Another concept that can potentially alleviate the above-mentioned problem is aerial assisted 6G communication networks, with the employment of e.g. unmanned aerial vehicles (UAVs). Providing connectivity to aerial users such as cellular connected UAVs is also a key challenge for tomorrow's cellular systems [28]. Concepts like adjoin beam-forming capable to provide content delivery to aerial users that exist together with several ground users, is under research. In this case a network that consists of massive multiple-input multiple-output (MIMO)-enabled ground BSs, which are uniformly distributed and are capable to serve both aerial and ground users through spatial multiplexing is investigated. Hypersurfaces, described next, can also be adopted to provide a software programmable, hence predictable, wireless environment.

8) HYPERSURFACES, INTELLIGENT SURFACES, ULTRA MASSIVE MIMO

Hypersurfaces (HSF) [29], Reconfigurable Intelligent Surfaces (RIS) [30]–[32], and Ultra-Massive MIMO [33], [34] are promising emerging hardware technology to improve the spectrum and energy efficiency of wireless networks. Ultra-Massive MIMOs use a large number of antenna arrays to change their radiation patterns over time and frequency, for both transmission and reception [33]. HSFs reconfigure the propagation environment of electromagnetic waves [29] through programmatically controlled metasurfaces to suit given objectives [16]. RIS, a related concept, comprises an array of RIS units, each of which can independently incur some change to the incident e-m signal [30]. HSF/RIS, in contrast to MIMOs, do not need any dedicated energy sources, and as they have no analog or digital circuitry they are also immune to noise, they have a large frequency response (Mhz to Thz), and due to their almost 2-D surface they can be deployed in walls and objects, indoor or outdoor in ground or aerial moving networks. Below we focus our discussion on HSFs.

Metasurfaces are thin film planar, artificial structures that have recently enabled the realization of novel electromagnetic (EM) and optical components with engineerable functionalities. These include total EM radiation absorption, filtering and steering, as well as nano-antennas for sensors and implantable devices. They constitute the state-of-the-art way for manipulating electromagnetic energy in completely custom manners, even in ways not achievable with solutions based on natural materials. Electromagnetic cloaking, for instance, constitutes a very well-known application example: an object is coated with a metasurface, making it completely invisible to electromagnetic waves.

Nonetheless, the impressive capabilities of metasurfaces remained "disconnected" from real-world applicability in a sense. There was no straightforward way of having a "plug-and-play" metasurface, that gets installed within an environment and actively alters it in an easy-to-integrate way. The recently proposed concept of HyperSurfaces provided an answer to this challenge by proposing a new hardware platform that can host metasurface functionalities described in software. The key ideas are: i) to make the hardware components compatible with existing connectivity standards, and ii) allow any software developer to integrate the capabilities of metasurfaces in novel applications.

HyperSurfaces model the physical capabilities of metasurfaces (e.g., their ability to manipulate electromagnetic waves by steering to custom reflection directions) in the form of software components, expressing them as "Virtual Metasurface Functions" [16]. Subsequently, they allow for the interplay of these functionalities, i.e., their configuration and combination over a metasurface via common communication protocols. Allowing for direct integration to control loops without requiring knowledge on Physics, the HyperSurfaces seek to bring the metasurface capabilities for manipulating electromagnetic waves to the 6G world. With these novel inteconnection capabilities added, HyperSurfaces introduced the first approach for internetworking metasurfaces. A novel problem that has been posed is the end-to-end configuration of HyperSurfaces, i.e., which types of wave manipulation functionalities to deploy at each HyperSurface unit, in order to maximize a wireless system's performance objectives. Examples include massive connectivity even in NLOS areas, near perfect interference cancellation and wireless power transfer. The proposed modeling approach is a complex multigraph [16], where HyperSurface units act as vertexes, and connectable HyperSurfaces are mapped to edges. Moreover, the graph is time-variant (due to changes in the environment such as user device mobility) and non-linear, meaning that the egress edge weights of a node are dependent on the ingress edge (wireless e-m wave arrival direction). Due to the peculiarities of the metasurface Physics, even simple path-finding processes in this type of graphs is a very complex process, requiring new approaches for its resolution.

III. BASIC CONCEPTS OF COMPLEX SYSTEMS

It is beyond any doubt that classical Physics, a traditional science discipline, has developed many successful tools for predicting the behavior of a system as a whole from the properties of its constituents. The success of this modeling is based on the simplicity of the interactions between the elements according to which there is no ambiguity as to what interacts with what, and the interaction strength is uniquely determined by the "physical distance" [35].

On the other hand, for many complex systems, including biological and man-made, with non-trivial network topology such ambiguity is naturally present. In the past few years many researchers studied the structure and function of complex networks [2] and they have increasingly recognized that the tools of complex theory offered a promising framework for describing these systems [36].

Nowadays, there is an increasing need to move beyond classical physics-based approaches and try to understand the behavior of the system as a whole. Towards this direction, understanding the topology of the interactions between the components is unavoidable. In accordance with [36], there are three basic concepts that occupy a prominent place in contemporary thinking about complex systems, which are defined below:

- **Small world:** According to [37] a small-world network is a type of mathematical graph where although most nodes are not neighbors of each others, their neighbors could be neighbors with the neighbors of the other nodes, and most nodes can be reached from every other node by a small number of hops or steps. The small-world concept, in simple terms, describes the fact that despite their often large size, in most networks there is a relatively short path between any two nodes. The distance between the two nodes is defined as the number of edges along the shortest path connecting them. The short path lengths also appear in random graphs, but in random graphs the clustering coefficient is considerably small due to the fact that edges are distributed randomly [38].
- **Clustering:** A common property of social networks is the cliques formed, which represents circles of friends or acquaintances in which every member knows every other member. The inherent tendency to cluster is quantified by the clustering coefficient [37], a concept that has its roots in sociology. The clustering coefficient of node i is the ratio of the actual number of edges connecting the nodes with their immediate k neighbors to the number of edges in a fully connected network of those k nodes, denoted by C_i:
$$C_i = \frac{2E_i}{k_i(k_i - 1)}, \tag{1}$$
where E_i is the number of edges leaving from node i towards its k_i neighbours. The clustering coefficient of the entire network is the average of all individual C_i's.
- **Degree distribution:** Not all nodes in a network have the same number of edges (same node degree). The spread in the node degrees is characterized by a distribution function $p(k)$, which gives the probability that a randomly selected node has exactly k edges.

Based on the aforementioned attributes, the three robust measures that are used to analyze a network topology are: average path length, clustering coefficient and degree distribution. All of the three concepts above are expected to apply in the context of 6G networks. The "Small World" concept is a concept that fully applies in the 6G networks since the expected development of "tiny cells" whose radius is only few meters as well as the network slicing can be considered as an application of the "Small World" concept. In this type of networks, the small-world network has a small mean distance between the nodes since the communication takes place though cellular hubs. This property is often analyzed by considering the fraction of nodes in the network that have a particular number of connections going into them (the degree distribution of the network). Networks with a greater than expected number of cellular hubs will have a greater fraction of nodes with high degree, and consequently the degree distribution will be enriched at high degree values. Regarding clustering, even though, there are a number of techniques used to attain better load, delay and throughput, as for example in WLANs (Wireless Local Area Networks) networks and 5G networks, the clustering of the nodes is considered as the best method, since it aims to reduce the delay and enhance the throughput as well as load and also increases the life span of the network [39]. Clustering is expected to dominate in 6G networks.

Below, we focus on complex adaptive systems, a special class of complex systems which are expected to play a central role in 6G.

IV. COMPLEX ADAPTIVE SYSTEMS (CAS) PROPERTIES

Complex adaptive systems can be seen as subsets of complex systems. They are complex in the sense that they are diverse and made up of multiple interconnected elements and adaptive in that they have the capacity to learn and change over time based on experience. Organized behavior emerges from the simultaneous interactions of elements without any global plan. Figure 3 depicts a complex adaptive system model which takes into account the internal and external processes and interactions. Artificial Intelligence (AI) and Machine Learning (ML) are fundamental adaptive properties of 6G networks.

Complex adaptive systems encompass many properties and the most important of them are listed below:

- **Many interacting parts:** The sole components of a system are known as elements as, for example, the air and water molecules in a weather system, the flora and fauna in an ecosystem and the many heterogeneous,

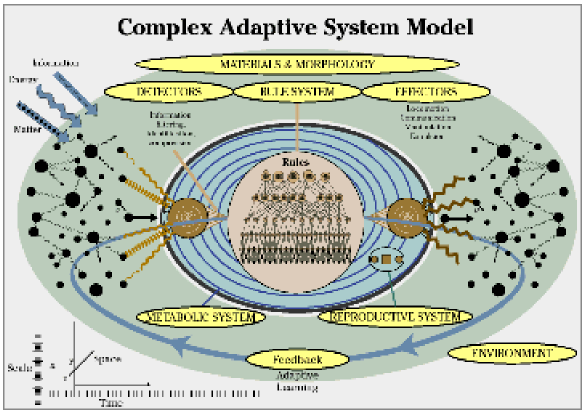


FIGURE 3. **Complex adaptive system model [40].**

dynamically interconnected nodes in 6G, which are arbitrarily interconnected. These elements interact with each other as well as with their environment in unpredictable and unplanned ways. But from this mass of interactions regularities emerge and start to form a pattern which feeds back on the system and informs the interactions of the elements. For example, in an ecosystem if a virus starts to deplete one species, this results in a greater or smaller food supply for others in the system which affects their behavior and their numbers. A period of flux occurs in all the populations in the system until a new balance is established.

- **Evolution and Cooperation:** A complex system consists of many interacting elements that may compete or cooperate in different times. This behavior is primarily based on the heterogeneity of the constituent components that have different attributes and capabilities and therefore depending on the particular cooperative links can potentially perform multiple and diverse tasks. Under these circumstances, evolution results from the process of creating linkages between elements so that the result will be successful in the environment. Therefore, the essential ability of an evolutionary network appears to be its capability to create cooperative links that lead to an overall successful result in the environment. Individuals are therefore searching for a situation in which they fit into the "inner" environment made up of the particular counterpart to which they are linked in the network, and also in which the overall effect of the partners working together fulfill some requirements in the external environment. Stability arises when each individual fits successfully in the counterpart, and the counterpart fits successfully in the wider environment. In case of external perturbations causing a change in the stable state of the environment, then the alliance as well as each individual that may participate within the alliance will need to evolve.
This discussion sheds light on the aspects concerning the interactions of individuals within a system which are bound to change the environment these individuals live in. By closing the feedback loop in the evolutionary explanation, a new mathematical theory of the evolution of complex adaptive systems arises. It is this general theoretical option that lies at the core of the emerging field of complex adaptive systems. Consequently, a major promise in the study of complex adaptive systems is to elucidate the long-term effects of the interactions among the evolutionary complex processes and provide causal explanations for phenomena that are highly improbable in common sense.
- **Emergent Behaviour:** Emergence is the process of deriving some new and coherent structures, patterns and properties in a complex system which were not previously observed. Emergent phenomena occur due to the pattern of interactions (non-linear and decentralized) between the elements of the system over time. More generally, it refers on how the behavior at a larger scale of the system arises from the detailed structure, behavior and relationships on a finer scale. One of the main points about emergent phenomena is that they are observable at a macro-level, even though they are generated by micro-level elements. In the extreme, it is about how macroscopic behavior arises from microscopic behavior.
- **Degeneracy:** According to [41], degeneracy is the ability of elements that are structurally different to perform the same function or yield the same output. It is a ubiquitous characteristic of biological systems, existing at all levels of biological organization, i.e. at genetic, cellular, system, and population levels, and that it is both necessary for, and an inevitable outcome of, natural selection. As a result, two primary degenerate system attributes are identified in [42]: system robustness without compromising efficiency; and increased adaptability based on providing multiple options to deal with changes. Hence, they argue that degeneracy enables robustness and evolution through diversity, essential properties of complex systems.
- **Adaptability:** In the most general sense, adaptation is a feedback process in which external changes in an environment are mirrored by compensatory internal changes in an adaptive system. In the simplest case, an adaptive system may act in a regulatory manner, like a thermostat, so as to maintain some property of the system at a constant level. An interesting type of adaptation is found in complex systems in which the interactions among the constituent elements are allowed to change. This process is very similar to a self-modifying program, since the actions of the adaptive unit can affect the environment, which, in turn, feeds information back to the adaptive system. Thus, adaptation, in this sense, can be seen as a computation of the most complex form that emerges through the multiplicity and recursion of simple elements or subsystems.
- **Self-Organization:** Self-organization is the evolution of a system into an organized form in the absence of external direction, manipulation or control. In other

words, the constraints on the organization of the system are internal phenomena, resulting from the interactions among the components and usually independent of their physical nature. The dynamics of a self-organizing system are typically non-linear, because of circular or feedback relations between the components. Two types of feedback loops exist, positive feedback loop and negative feedback loop. In a positive feedback loop the system responds in the same direction as the perturbation. The end result of a positive feedback is often amplifying and "explosive". That is, a small perturbation will result in big changes. This feedback, will drive the system even further away from its own original set-point, thus amplifying the original perturbation signal, and eventually to become explosive because the amplification often grows exponentially (with the first order positive feedback), or even hyperbolically (with the second order positive feedback). On the other hand, in negative feedback loop the system responds in an opposite direction to the perturbation. It is a process of feeding back to the input a part of a system's output, so as to reverse the direction of change of the output. This tends to keep the output from changing, so it is stabilizing and attempts to maintain constant conditions. This often results in equilibrium (in physical science) or homeostasis (in biology) such that the system will return to its original setpoint. While self-organization will often be in response to the system's environment, it will not be directly controlled by the environment nor has it been designed by someone outside the system. A complex adaptive system is continually self-organizing through the process of emergence and feedback. The research on self-organization tries to find general rules about the growth and evolution of systemic structures, the forms it might take, and seeks for methods that may predict the future results of self-organizing processes.

- **Decentralization:** Decentralized operation can provide a degree of scalability and robustness that cannot be achieved with centralized architectures. Decentralization achieves modularity and increases reliability by reducing explicit dependence on a few central nodes. In particular, it can permit a network of nodes to exchange information and coordinate activities in a flexible and scalable architecture that would be impractical or impossible to achieve with a single, monolithic systems platform. Moreover, decentralized systems provide adaptability and intelligence as the system can be 'smarter' than its constituent smartest element. It is worth to mention that decentralized and distributed systems are two different approaches. In distributed systems, the decision is made by a negotiation process between the executive components and executed by them. In decentralized systems each executive component makes its own decisions and executes only these decisions.
- **Robustness:** Robustness refers most commonly to the structural and other properties of a system that allow it to withstand or tolerate stress, perturbations or variations in its internal structure or external environment without malfunctioning but at the same time without in any way durably changing either its structure or its dynamics. In other words, it is the ability of a networked system to sustain a giant component. Recent work on network theory has started to address the question of the robustness of complex networks to failure and directed attacks. It suggests that the network connectivity, and hence its functionality, is robust against random failure of nodes [43]–[45] and to some extent is even robust against intentional attacks [46]. Moreover, researches [47] showed that for many physical networks, the removal of nodes can have a much more devastating consequence when the intrinsic dynamics of flows of physical quantities in the network is taken into account.
- **Resilience:** As defined by [48], resilience refers to *"the capacity of a system to absorb and utilize or even benefit from perturbations and changes that attain it, and so to persist without a qualitative change in the system structure."* Such a system may, however, take new external conditions into account by absorbing them into its mode of functioning. The difference (if any) between resilience and robustness thus seems to lie in the extent to which (non-structural) changes in the dynamics may be introduced into a system under the impact of changes in external circumstances. When networked systems break down or are subject to attack, problems can cascade throughout the infrastructure, capable of disabling the network almost entirely. Under these circumstances, resilience can be seen as the ability of systems to respond in ways that rectify themselves or rapidly contain the consequences of the accident or deliberate disruption and keep operative at an acceptable level. Recently, there has been much interest in the resilience of real-world networks to failure of nodes or to intentional attacks [43]–[45].
- **Non-linearities:** Complex adaptive systems are governed by non-linear interactions. Therefore, the output of such a system is not proportional to its input. This deduction is driven by the observation that we cannot predict how a system will work by understanding the behavior of the constituent elements separately, and combining them additively. Furthermore, a salient property of most dynamical processes in complex systems is their almost unavoidable nonlinearity. Part of the recent interest in the study of dynamics on complex networks comes from the understanding that techniques and expertise developed in the study of nonlinear dynamics and chaos can be useful in the study of such nonlinear systems.

5G and 6G mobile communication networks are complex adaptive systems where all the concepts presented above apply to some degree. The 5G and 6G networks can be engineered, analyzed and modeled at a degree within the complex systems framework and hence provide for a more predictable and controllable network.

Next, we will focus on the characterization of various network models, which created considerable attention within the networking world.

V. SPECIFIC NETWORK MODELING PARADIGMS

Recent advances in the characterization of complex systems have given rise to the revival of network modeling, resulting in the introduction and study of five main classes of modeling paradigms, expected to be relevant to 6G.

A. RANDOM NETWORKS

For more than 40 years, science treated complex networks as being completely random. This paradigm has its roots in the work of Alfred Renyi and Paul Erdos ([49], [50]) who addressed for the first time in history one of the most fundamental questions pertaining to our understanding of our interconnected universe: How do networks form? Their solution laid the foundation of the theory of random networks which came to dominate our idea on network modeling.

Those pioneering studies of network structure were focused on random networks, of which nodes have equal probability of connecting with each other. Random networks, which are variants of the Erdos-Renyi model [49], [50], are still widely used in many fields and serve as a benchmark for many modeling and empirical studies. This paradigm of network modeling can be characterized by (a) a low average path length, (b) a small clustering coefficient, and (c) a degree distribution following a Poisson distribution with a bell shape as depicted in Fig. 4. The latter characteristic reveals that although not all nodes in this kind of network would be connected to the same degree, most would have a number of connections hovering around a small, average value.

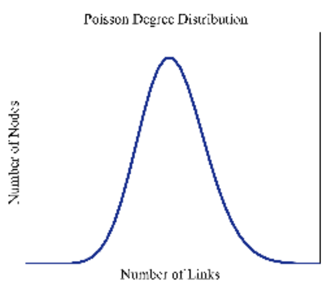


FIGURE 4. Poisson degree distribution.

Random networks are robust to coordinated attacks (that is, to the selection and removal of a few nodes that play a crucial role in maintaining the network's connectivity) [51] but on the other hand are intolerant to accidental failure due to the fact that they are not highly interconnected. Specifically, the connectedness of a randomly distributed network decays steadily as nodes fail, slowly breaking into smaller, separate domains that are unable to communicate.

B. SMALL-WORLD NETWORKS

Motivated by the inefficiency of both random networks and regular lattices to provide an adequate framework within which to study real-world complex networks, a new class of models collectively called small-world models was introduced by Watts and Strongatz in 1998 [37]. Small world models interpolate between the highly clustered regular lattices and random graphs (as shown in Fig. 5). In particular, these models have a high degree of local clustering or cliqueness (like a regular lattice network) and a relatively short average minimum path (like a completely random network) often socialised in the literature to the 'six degrees of separation' property.

In their pioneering article [37], Watts and Strongatz studied a simple model starting from an ordered finite-dimensional ring lattice with N nodes connected to their first K neighbors (having $N \gg K$) as shown in Fig. 5a and replacing the original links by random ones with some probability $0 \leq p \leq 1$. By varying p, Watts and Strongatz could closely monitor the transition between order ($p = 0$ and Fig. 5a) and randomness ($p = 1$ and Fig. 5c). They found that this model paradigm is able to transform a 'sparse' network (i.e. a regular lattice with $N \gg K$) into a small-world with relatively short paths between any two nodes by setting p between zero and 1 ($0 < p < 1$ and Fig. 5b). Moreover, the new model was found to be much more highly clustered than a random graph.

According to Watts and Strogatz [37], *"models of dynamical systems with small-world coupling display enhanced signal propagation speed, computational power, and synchronizability."* These findings have profound implications for many real systems. In a telecommunication network for example, 'small-world connectivity' might improve the ease with which data diffuses through the system. In a transportation network, 'small-world topology' could improve the flow of people or goods through the network.

Taking all these into consideration, the obvious inference is that the Watts and Strogatz model addresses the connectivity issue of a network but on the other hand it does not say anything on how nodes would use shortcuts to reach remote nodes. Similarly, there are some important issues that are not addressed by the small-world model as, for example, the affect of mobility on the small-world networks as well as the robustness, efficiency and scalability of those networks.

In principle, small-worlds networks are characterized by (a) a high clustering coefficient like regular lattices, and (b) a short characteristic path length as well as a degree distribution typical of random networks. It is believed that many real world networks including social networks (e.g. film actors), the electrical power grid, and the neural network of the nematode worm C.elegans (studied in [37]), exhibit small-world phenomenon, but the real challenge is how to impose it on an engineered dynamic system as, for instance Mobile Ad-hoc Networks (MANETs) or Wireless Sensor Networks (WSNs), or even 5G and 6G networks.

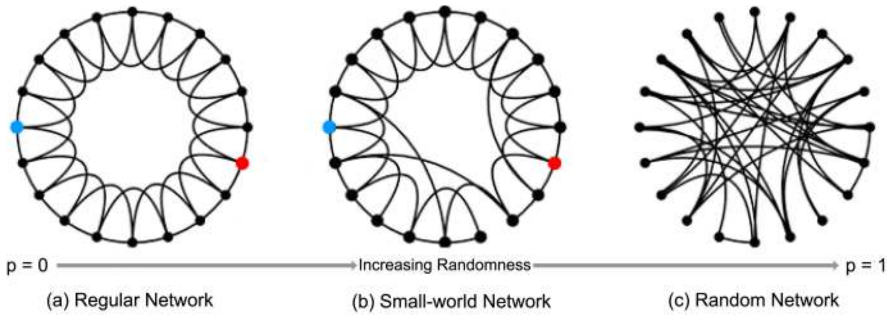


FIGURE 5. A small world network is between a regular lattice network and a random network. After [37].

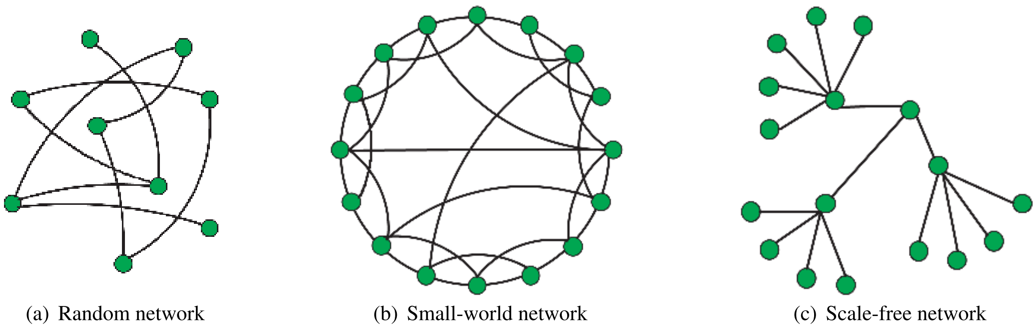


FIGURE 6. Network modeling paradigms.

C. SCALE-FREE NETWORKS

In the late 1990s, attempts were made to explore and explain the structure of the World Wide Web. Researchers tried to apply the concept of small worlds to explain the functionality of the web, but this didn't quite work, although the web was considered a small-world rather than a random network. The reason was that in the small-world model of Watts and Strogatz, each node has only a few connections compared to the total number of nodes in the system as can be seen in Fig. 6.

Those research efforts led to one of the most interesting developments in the understanding of complex networks; the discovery that for most large networks the degree distribution significantly deviates from a Poisson distribution. In particular, for a large number of real networks, including the World Wide Web (WWW) [52], the Internet [53], the mail network [54], [55], etc., the degree of distribution was found to follow a power-law tail, $p(k) \sim k^{-\gamma}$ as illustrated in Fig. 7, which defines the probability of a node having k edges. These network topologies that exhibit power-law distributions in the connectivity of network nodes were originally introduced by Barabasi and Albert [56] as generic, yet universal network models called scale-free models, aiming to offer a universal theory of network evolution by focusing on the network dynamics. At this point it is important to mention that according to the latest research work [57] the theories presented above may not be as valid for the Internet since, as it is shown in [57], recent measurements indicate that the Internet ecosystem is rapidly evolving from a multi-tier hierarchy built

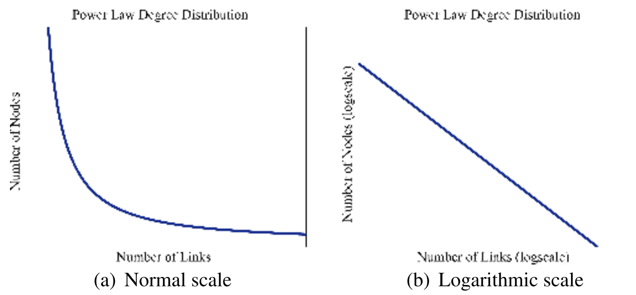


FIGURE 7. Power-law tail.

mostly with transit (customer-provider) links to a dense mesh formed with mostly peering links. In this work, authors, study this evolutionary transition with an agent-based network formation model. The suggested model predicts several substantial differences between the Hierarchical Internet and the Flat Internet in terms of topological structure, path lengths, interdomain traffic flow, and the profitability of transit providers. Another work that reinforces the statement above is presented in [58]. In this work authors claim that scale-free networks are rare. This statement is based on the work they have performed to study the universality of scale-free structure by applying state-of-the-art statistical tools to 1000 network data sets of different categories. According to their results they found that scale-free networks are rare, with only 4% exhibiting the strongest-possible evidence of scale-free structure and 52% exhibiting the weakest-possible evidence.

Contrary to the model of small-world networks which introduces isolated clusters of highly interconnected nodes,

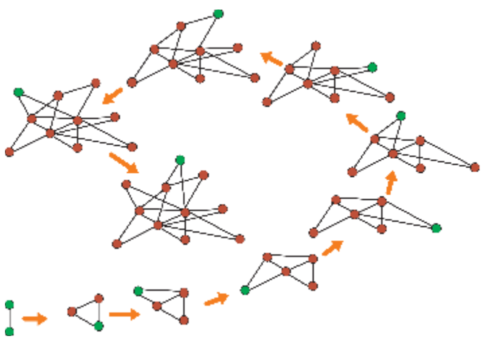


FIGURE 8. Birth of a scale-free network based on Barabasi-Albert model [59].

scale-free networks consist of highly connected hubs that hold together the network. It seems that these two network theory approaches run counter, but can also be compatible, as stated in [59], which demonstrates that *"a network can be both highly clustered and scale-free when small, tightly interlinked clusters of nodes are connected into larger, less cohesive groups. This type of hierarchy appears to exist in a number of systems, from the World Wide Web (in which clusters are groupings of web pages devoted to the same topic) to a cell (in which clusters are teams of molecules responsible for a specific function)"*.

The random and small-world networks models are formed by a fixed number of nodes N, that are randomly connected or rewired. Additionally, it is assumed that new edges are placed randomly, something which more specifically means that the probability that two nodes are connected (or their link is rewired) does not depend on the node's degree. These two assumptions do not apply in most real world networks as, for example, the Internet and the World Wide Web. Towards this direction, a variety of approaches for generating ensembles of graphs having scale-free characteristics have been proposed including the preferential attachment (Barabasi-Albert model [56]), power-law random graph [60], the linearized chord diagram (LCD) model [61], etc.

1) BARABASI-ALBERT (BA) MODEL

The first and perhaps the most studied of the models in this vein, is the Barabasi-Albert model [56]. This model is based on two key features, namely growth and preferential attachment which are shown in Fig. 8. The term growth refers to the continuous addition of new vertices and edges to the network, as for example, the WWW grows exponentially by adding new web pages. In addition, according to the preferential attachment mechanism, new nodes added into a network have higher probability of connecting to the existing nodes with high connectivity, i.e., a 'rich-gets-richer' phenomenon. For example a newly created web page will more likely include links to well known, popular documents with high connectivity.

Thus, the topology of Barabasi-Albert networks grows by the continuous addition of new nodes starting from a small number of nodes which increases throughout the lifetime of the network. The connection or rewiring of the nodes takes into account the preferential attachment mechanism, such that the likelihood of connecting to a node depends on the node's degree, i.e. the likelihood is proportional to the number of links that the existing node already has. Therefore, heavily linked nodes (called hubs) tend to quickly accumulate even more links, while nodes with only a few links are unlikely to be chosen as the destination for a new link. It is as if the new nodes have a 'preference' to attach themselves to the already heavily linked nodes. This is apparent in Fig. 6c, which reveals that the nodes of a scale-free network aren't randomly or evenly connected but the degree distribution (number of links per node) follows a power law.

As implied by the Barabasi-Albert model, scale-free networks consist of a relatively small number of highly connected nodes, hubs of connectivity and a large number of low degree nodes which are accumulated around hubs. Scale-free networks are characterized by (a) a low average path length, (b) varying clustering coefficient - but much larger than in random networks - depending on other topology details (it decreases as the node degree increases), and (c) a power-law degree distribution. Based on their inhomogeneous topology, scale-free networks can be amazingly robust against random failures. In particular, since failures occur at random and the vast majority of nodes are those with small degree, the likelihood that a hub be affected is almost negligible. Even if such event occurs, the network will not lose its connectedness, which is guaranteed by the remaining hubs. Simulations on scale-free networks [59] reveal that even if as many as 80 percent of randomly selected routers within the Internet fail, the remaining ones still form a compact cluster in which there will still be a path between any two nodes. On the other hand, the presence of hubs makes the scale-free networks more vulnerable to targeted attacks. To this extend, if we choose a few major hubs and take them out of the network (targeted attack), it simply falls apart and is turned into a set of rather isolated graphs. Therefore, there is an imperative need to protect the Achilles' heel of scale-free networks against malicious targeted attacks in order to maximize the network lifetime. This of course should be based on further analysis, for example, on determining how many hubs are essential for the liveness of a given network.

Despite the fact that the Barabasi-Albert model has been extensively studied, most of the related work appears to be of a heuristic or experimental rather than mathematical nature. Several heuristic and experimental studies on the Barabasi-Albert model can be found in the extensive surveys [36] and [62]. In contrast, so far there has been rather little rigorous mathematical work; what there is sometimes confirms and sometimes contradicts the heuristic results. See [60], [63]–[65] and [66] for some examples, or the survey [67].

2) OTHER MODELS

Aiello and Lu [60] proposed a random graph model which is a special case of sparse random graphs with given degree

TABLE 1. Scale-free networks are everywhere. After [59].

Network	Types	Nodes	Links
Cellular Metabolism	Biology	Molecules involved in burning food for energy	Participation in the same biochemical reaction
Protein regulatory	Biology	Proteins that help to regulate a cell's activities	Interactions among proteins
Sexual relationships	People	People	Sexual contact
Hollywood	People	Actors	Appearance in the same movie
Research collaborations	People	Scientists	Co-authorship of papers
Internet infrastructure	Technology	Routers	Optical and other physical connections
World Wide Web	Knowledge	Web pages	URLs

sequences that satisfy a power-law. This model involves only a small number of parameters, called logsize and log-log growth rate. These parameters capture some universal characteristics of massive graphs. The study of these parameters reveals what other network properties can be derived from its scale-free nature.

Moreover, a precisely defined model, the linearized chord diagram or LCD model, was introduced in [61], motivated by the Mobile User Equipment (UEs), Ultra-Dense cells, BSs, vague description of Barabasi-Albert, and incorporating its key features as well as other useful mathematical properties. The LCD model considers two basic characteristics of a precise version of the Barabasi-Albert model from the mathematical point of view, namely robustness to random damage, and vulnerability to malicious attack.

Further elaboration of scale-free models which arise from attempts to explain the power law, starting from basic assumptions about the growth of the graph is given in the survey [67].

D. DYNAMIC COMPLEX NETWORKS THAT CAN HANDLE MOVING NETWORKS

The extraordinary expansion of the Internet in both the size and the offered services and its flexibility in accommodating a number of heterogeneous technologies leading to network convergence, has gradually led to a change in its architectural paradigm shifting from "rigid hierarchical - hardware first - to a more flat and flexible- software first – implementation" [42]. This shift, which is expected to further evolve as we gradually move beyond 5G towards 6G, necessitates the adoption of complex networks analytical models and tools beyond the aforementioned ones. User mobility and miniaturization have been pivotal in driving this paradigm shift, promoting the need for adaptivity and re-configurability. Recent trends imply that mobility may not simply apply to the end hosts which is the common case (often strongly coupled to human mobility), but can now also apply to the intermediary devices, as for example moving base stations mounted on UAVs or even mobile phones serving as base stations [68] leading to the ideas of **moving networks** [26] and **proximity networks**. "Proximity networks are time-varying graphs representing the closeness among humans moving in a physical space" [69] and significant research efforts have been reported in the literature to characterize their applicability e.g. in message spreading [70] and statistical properties, revealing complex systems methodologies as for example power laws [71]. Further, modern complex network theory tools can be used to account for these effects leading to more effective designs. The fields of Temporal Networks (graphs) [72], [73], Dynamic Network Analysis [74] and Evolutionary Graph Theory [75] are highly relevant to the current Dynamic Internet, however, new theoretical tools may still need to be developed to account for the specifics of the considered problem [69], [76].

E. HYBERBOLIC GEOMETRY OF COMPLEX NETWORKS

The latest and most promising work is presented in [77]. In this work the authors developed a geometric framework to study the structure and function of complex networks. They assumed that hyperbolic geometry (Fig.9) underlies these networks, and they showed that with this assumption, heterogeneous degree distributions and strong clustering in complex networks emerge naturally as simple reflections of the negative curvature and metric property of the underlying hyperbolic geometry.

Conversely, they showed that if a network has some metric structure, and if the network degree distribution is heterogeneous, then the network has an effective hyperbolic geometry underneath. Then, they established a mapping between their geometric framework and statistical mechanics of complex networks. This mapping interprets edges in a network as non-interacting fermions whose energies are hyperbolic distances between nodes, while the auxiliary fields coupled to edges are linear functions of these energies or distances. The geometric network ensemble subsumes the standard configuration model and classical random graphs as two limiting cases with degenerate geometric structures. Finally, they showed that targeted transport processes without global topology knowledge, made possible by their geometric framework, are maximally efficient, according to all efficiency measures, in networks with strongest heterogeneity and clustering, and that this efficiency is remarkably robust with respect to even catastrophic disturbances and damages to the network structure. The above theory can fully apply in 6G networks since heterogeneity and clustering are concepts that dominate these type of networks.

VI. MOBILE COMMUNICATION NETWORKS AS COMPLEX SYSTEMS

Inspired by the recent advances in complex theory, we should take a deeper look at the communication network anatomy and how this may apply in complex mobile communication networks. It is beyond any doubt that network anatomy is important to be characterized, because the structural and evolutionary properties of networks are considered to affect their function. This study should be embraced by the interplay between the dynamics and the structure of complex networks. In fact, in the last few years it became clear that in spite of the inherent differences, most real communication networks, as, for example, the Internet [53], the World Wide Web (WWW) [52], and the mail network [54], [55], are characterized by similar topological properties as in the complex networks structures.

Complex networks are generally characterized by large scale topologies, decentralized/distributed resource management, extreme heterogeneity of the constituent elements, relatively small characteristic path lengths, high clustering coefficients, power-law degree distributions, modularity etc., which are all properties highly correlated to real communication networks too. Attempts to explain such similarities may be fueled by the study of universal structural properties in real communication networks as well as by the theoretical understanding of evolutionary laws governing the emergence of these properties.

A. COMPLEX NETWORK ATTRIBUTES

In general, communication networks are characterized by a chain of possible complex attributes that can be viewed from the perspective of complex (adaptive) networks. These attributes are illustrated below:

- **Structural complexity:** The overwhelming majority of communication networks have complex topology. As far as the structural properties are concerned, there was an increasing voiced need to pay attention to the evolutionary mechanisms that have shaped the topology of a network, and to the design of new models based on a theoretical foundation as for example random networks [49], [50], small-world networks [37], and scale-free networks [52], [56], which retain the most significant properties observed empirically. This research was motivated by the expectancy that the characterization and the modeling of the structure of a network would lead to a better knowledge of its dynamical and functional behavior.

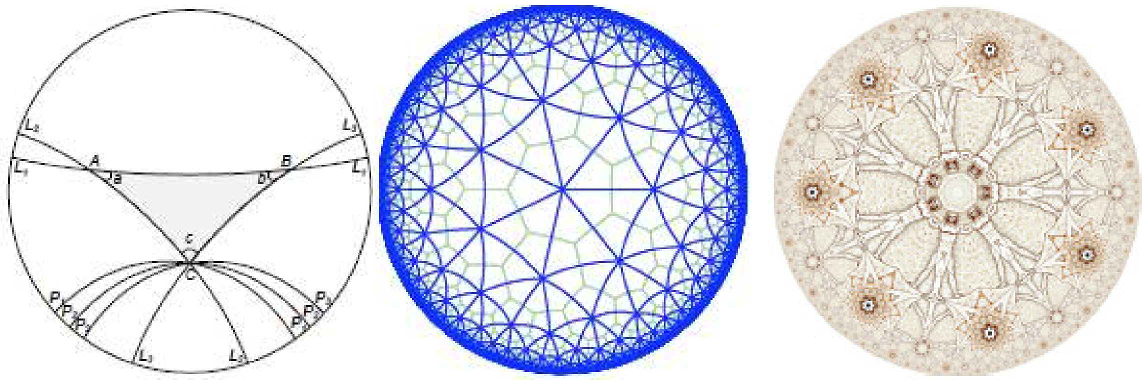
  Furthermore, the structural complexity of a network can be influenced from both node and connection diversity. Multiple complications can be observed due to the fact that a network can consist of different kinds of nodes which can be interconnected through links having different weights and directions, resulting in a high level of heterogeneity.

  Consequently, even the wiring diagram of a network is considered to affect its functional robustness and resilience to external perturbations, such as random failures, or targeted attacks. At the same time, the network topology plays a crucial role in determining the emergence of collective dynamical behavior, such as synchronization, or in governing the main features of relevant processes that take place in complex networks, as, for example, the spreading of information.

  Apparently, it remains a challenge to answer some fundamental questions as, for example, 'How does one characterize the wiring diagram of such networks?', or 'Are there any unifying principles underlying their topology?'.
- **Network evolution:** The wiring diagram of a communication network is subject to dynamic changes over time. This is a basic characteristic of dynamically changing environments like, for example the WWW or the mobile network, where links are created and lost over time. From this point of view, the evolution of a communication network can be paralleled with the evolution of a complex (adaptive) network which is considered to be very sensitive to initial conditions or to small perturbations, leading to multiple pathways by which the system can evolve.
- **Dynamical complexity:** The network and each node within it could be non linear dynamical systems which their state may vary over time as a result of the evolution. The understanding of the evolutionary laws governing the emergence of the structural properties could be based on the study of dynamical processes of complex networks. In this context, network problems in traditional areas such as robust flow and congestion control, fault and attack tolerance, error resilience, decentralized/distributed operation, which are just in the forefront of the current research on network dynamics, are prime candidates to be addressed based on concepts arising from the dynamical processes of complex networks.

  To this end, from the perspective of non linear dynamics, we would like to understand how an enormous network of interacting dynamical systems (e.g., mobile user equipment (UEs), mobile nodes, ultra-dense cells, BSs, sensor nodes, routers, etc.) will behave collectively, given their individual non linear dynamics and coupling architecture.

All the aforementioned attributes of networked systems remain open challenges which potentially can be effectively addressed by complex systems theory. Powerful new ideas and techniques can be found by studying the similarities between communication networks and other complex systems. In this respect, complex systems science can be seen to bridge the gaps between the natural, social and formal sciences, and especially between engineering and the sciences.



(a) $L_{1,2,3}$ and $P_{1,2,3}$ are examples of hyperbolic lines

(b) $\{7,3\}$-tessellation of the hyperbolic plane by equilateral triangles, and the dual $\{3,7\}$-tessellation by regular heptagons are shown

(c) the exponentially increasing number of men illustrates the exponential expansion of hyperbolic space. The Poincare tool [78] is used to construct a {7,7} -tessellation of the hyperbolic plane, rendering a fragment of The Vitruvian Man by Leonardo da Vinci

FIGURE 9. Poincare disk model [77].

B. COMPLEX NETWORK DESIGN PRINCIPLES

Our increasing ability to address the aforementioned challenges are based on some basic features of complex systems which were discussed earlier to some extend, such as 1) self-organization and adaptability, 2) robustness and resilience, 3) decentralized/distributed operation and 4) engineering self-organisation and emergent behaviour. These features are analyzed below and may be seen as the main design principles of contemporary networked systems. The study of these features - from complex systems perspective - is based on a combination of the growing mass of empirical data which has recently become accessible, and the large increase in computational power which can support and underpin significant advances in the theoretical understanding of complex systems.

Given the emergent design of 6G networks, it is imperative that these powerful tool be adopted at an early stage for its design and analysis and also for 5G with emerging and adopted system functionalities.

1) SELF-ORGANIZATION AND ADAPTABILITY

Self-organization refers to the evolution of a system into an organized form in the absence of external directives. Self-organization leads a system from a large region of state space to a persistent smaller one, under the control of the system itself. This smaller region of state space is called an attractor.

There are three major principles of self-organization mechanisms: feedback loops, local state evaluation, and interaction between individuals. One major component in understanding the interaction of components producing a complex pattern are positive and negative feedback loops as shown in Fig. 10. As explained in Section IV, positive feedback acts as an amplifier for a given effect (or perturbation), leading to an explosive growth. This feedback, will drive the system even further away from its own original setpoint, thus amplifying the original perturbation signal, and eventually become explosive. In negative feedback loop the system responds in an opposite direction to the perturbation. It is a process of feeding back to the input a part of a system's output, so as to reverse the direction of change of the output. This tends to keep the output from changing, so it is stabilizing and attempts to maintain constant conditions. This often results in equilibrium such that the system will return to its original setpoint. In fact, negative feedback is used to efficiently control the system behavior in order to prevent over-reactions and mis-regulations. The second ingredient is the local state. This means that all subsystems acquire and act upon information that is stored locally. Any global control or dependency is prevented in order to enable fully autonomous behaviour embedded into a global context. Information transfer between individuals is necessary to update the local state. There are two ways to conduct such interactions: direct interaction or communication between related subsystems and indirect information exchange by interacting with the environment [79].

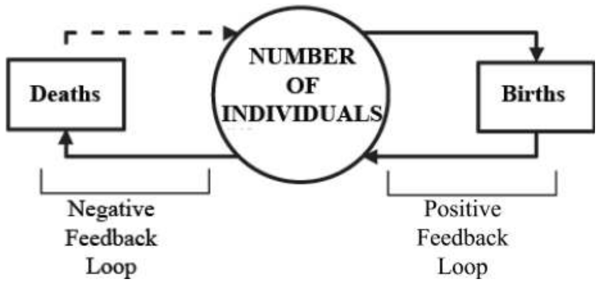


FIGURE 10. System control using positive and negative feedback loops. After [80].

Because of its decentralized character, self-organization tends to be robust, resisting perturbations. A self-organizing system is typically driven by non-linear dynamics, because of circular or feedback relations between the constituent components. Non-linear systems have in general several stable states, and this number tends to increase as an increasing input of energy pushes the system farther from its equilibrium.

Adaptability allows for the modification of a system's behavior in order to adapt to requirements posed by exogenous factors (e.g. users of a network) or environmental changes. Therefore, adaptation may be driven by users to provide them flexibility and ensure that their exact requirements will be fulfilled. Furthermore, to adapt to a changing environment, a system needs a variety of stable states that is large enough to react to all perturbations but not so large as to make its evolution uncontrollably chaotic. The most adequate states are selected according to their fitness, either directly by the environment, or by subsystems that have adapted to the environment at an earlier stage.

Formally, the basic mechanism underlying self-organization is the (often noise-driven) variation which explores different regions in the system state space until it enters an attractor. This precludes further variation outside the attractor, and thus restricts the freedom of the system components to behave independently. This is equivalent to the increase of coherence, or decrease of statistical entropy, that defines self-organization.

The study of such complex methodologies promises to enable more scalable self-organizing communication network infrastructures. Especially in the area of complex communication networks that are subject to dynamic topology changes (e.g., 5G/6G, ad-hoc, sensor networks and the Internet of Things), such solutions are considered of prime importance in order to enable them to simplify development and deployment. Self-organization and adaptability promise to drive the implementation of novel autonomously evolving mechanisms, capable of coping with global tasks (emergent behavior).

In the last few years, there was an increasing need to develop robust and efficient techniques which would be able to address various issues as, for example, congestion/overload control, data dissemination, quality of service (QoS) provision, power consumption, etc., in the forthcoming pervasive networking world. Given the often large number of perturbations that influence the structure and operation of a networked system, it became obvious that the implementation of the aforementioned techniques should be done on the basis of self-organization and adaptability. Towards this direction, the goal is to "teach" each node belonging to the network to self-organize for performing the requested tasks like event detection, periodic/continuous measurements, control and tracking taking into consideration energy and QoS constraints, i.e. showing an emergent global behavior [81].

Motivated by recent studies on complex nature and biological systems, researchers strive to adopt and apply the underlying principles to engineering and computer science, especially for self-organization. The combination of nature and self-organizing technical systems was first introduced by Eigen and Schuster [82]. In a recent study, Gerherson and Heylighen [83] provides a discussion on when and how to best model a system as self-organizing, and argues that self-organizing systems, rather than other type of systems, are a perspective for studying, understanding, designing, controlling, and building systems. The study of nature and biologically-inspired systems is as diverse as nature; it counts on the artificial immune system [84], swarm intelligence [80], evolutionary (genetic) algorithms [81], [85], [86], and cell and molecular biology based approaches [87]. Early attempts include the study of the behavior of swarms of insects, typically ants and bees, in an attempt to adapt the discoveries to build more efficient sensor networks [88], [89], to bird flocking for congestion control [81]. Furthermore, a special form of biologically-inspired computing with organic properties, namely organic computing [90] is attempting to build high-scalable architectures, which are self-organizing, self-maintaining, and self-healing. According to [91], typical features of self-organization include: (a) absence of external control (autonomy), (b) dynamic operation (time evolution), (c) fluctuations (noise/searches through options), (d) symmetry breaking (loss of freedom/heterogeneity), (e) global order (emergence from local interactions), (f) dissipation (energy usage/far-from-equilibrium), (g) instability (self-reinforcing choices/nonlinearity), (h) multiple equilibria (many possible attractors), (i) criticality (threshold effects/phase changes), (j) redundancy (insensitivity to damage), (k) self-maintenance (repair/reproduction metabolism), (l) adaptation (functionality/tracking of external variations), (m) complexity (multiple concurrent values or objectives), and (n) hierarchies (multiple nested self-organized levels).

2) ROBUSTNESS AND RESILIENCE

The robustness and resilience of critical infrastructures (e.g. real communication networks) in particular, and complex networks in general, are issues of great importance. Complex communication networks seem to display a high degree of robustness and resilience even though key components regularly malfunction and local failures rarely lead to loss of the global information-carrying ability of the network. This property of complex networks is often attributed to their design (i.e. the redundant wiring of their underlying network structure) and evolution. However, even though they remain unaffected by random component failures, they seem vulnerable to targeted attacks on its key components. Nevertheless, it remains an open challenge to identify whether and to what extent the network topology - beyond redundancy - is able to play a substantial role in the robustness and error/attack tolerance of such complex systems.

Recent work on network theory has started to address primarily the topological aspects of robustness and resilience in complex networks with respect to failure and directed attack caused by edge and/or node removal.

Initial efforts towards this direction were made by [49] and [92] addressing the reliability of a network with respect to edge removal based on random graph theory. The network model used in these early investigations was a randomly connected graph H_N consisting of N nodes. By removing a p fraction of edges, the researchers were seeking to evaluate the probability that the resulting subgraph is connected and extract any dependencies among connectedness and the removal probability p. Results carried out by [92] revealed that a broad class of H_N graphs displays a threshold-oriented behavior. In particular, a threshold probability $p_c(N)$ exists, such that for $p < p_c(N)$ the subgraph remains connected, but for $p > p_c(N)$ the subgraph is considered fragmented similar to phase transition phenomena, which abound in nature.

Needless to say that the removal of a single edge is not considered as harmful as the removal of a node. In the latter case, the effects on the robustness of an arbitrary graph are even more devastating, since the removal of a node results in the malfunctioning of all the edges attached on it as well. The effects of node removal have been recently studied with respect to random graphs and scale-free networks addressing their robustness against accidental node failures and intentional attacks.

Because of its immediate practical consequences to Internet and distributed systems, the problem of characterizing the robustness and error tolerance of complex networks has received growing attention, especially after the seminal papers by Crucitti *et al.* [43], who addressed node removal in scale-free models of Internet, and Callaway *et al.* [45] investigation on exponential networks under attack. Other related works include Holme and Kim [93] comprehensive comparative investigation of the resilience of several types of networks considering different schemes for attacking nodes and edges, and Cohen *et al.*'s analysis of Internet breakdown [44]. Works targeting specific types of network include, but are not limited to, Newman's investigation of e-mail networks [94], Jeong *et al.* study of metabolic systems [95], and Dunne's analysis of food webs [96]. More recently, the concept of L-expansions of a complex network was suggested [97] which, by enhancing the network connectivity, was believed to present good potential for increasing the resilience of existing networks. Moreover, Motter and Lai [47] showed that for many physical networks, the removal of nodes can have a much more devastating consequence when the intrinsic dynamics of flows of physical quantities in the network is taken into account.

These studies suggested that the network connectivity, and hence its functionality, is robust against random failure of nodes, and to some extent is even robust against intentional attacks. Results revealed that real networks (e.g. Internet) are naturally evolved to be quite resistant to random failure of nodes, but the presence of a few nodes with exceptionally large load, which is known to be ubiquitous in natural and man-made networks, has a disturbing side effect: the attack on a single important node with high load may trigger a cascade of overload failures, capable of disabling the network almost entirely. Such an event has dramatic consequences on the network performance, because the functionality of a network relies on the ability of the nodes to communicate efficiently with each other.

More specifically, Crucitti *et al.* [43] studied error and attack tolerance in exponential (random) and scale-free networks. They demonstrated that complex communication networks which incorporate a scale-free behavior, such as the Internet and the WWW, display a surprising degree of robustness, even though some significant constituent components are regularly subject to malfunction and local failures rarely lead to the loss of global information-carrying ability of the network. In order to address the error tolerant characteristic of exponential and scale-free networks, they studied the changes in their diameter (the average length of the shortest paths between any two nodes in the network), when a small fraction f of nodes was randomly or intentionally removed. Measurements revealed that in case of random node removal in exponential networks, the diameter increases monotonically with f, despite their redundant wiring. This behavior is rooted in the homogeneity of such networks: since all nodes have approximately equal number of edges attached on them, they all contribute equally to the network's diameter, thus the removal of each node causes the same amount of damage. On the other hand, scale-free networks display a totally different behavior. It was illustrated that scale-free networks including the Internet and the WWW, display an unexpected degree of error tolerance against random failures due to their inhomogeneous (power-law) connectivity distribution. Such networks display an unexpected degree of robustness, such that their ability to communicate to high failure rates remains unaffected even by unrealistically high failure rates. However, these networks are extremely vulnerable to directed attacks since their diameter increases rapidly, doubling its original value if 5% of the nodes are intentionally removed. On the contrary, measuring the diameter of an exponential network, they found that owing to their homogeneity, there is no substantial difference whether the nodes are removed randomly or in decreasing order of connectivity.

3) DECENTRALIZED OPERATION AND CONTROL

Complex networked systems consist of similar components which directly interact with their nearest neighbors. Even when these components interact with their neighbors in a simple and predictable fashion, the resulting system often displays complex behavior when viewed as a whole.

Decentralized operation and control are considered to be inextricable ingredients of complex networks since they provide resistance against perturbations (robustness and resilience). In fact, decentralization is the process of dispersing decision-making closer to the point of service or action.

This feature of complex communication networks allows flexibility that facilitates self-organization. Such flexibility is facilitated by lack of dependency on central decision-making. However, it has to be done in a manner that allows some control. This control may arise through the self-organization itself, or through the interaction between components that is enabled by self-organization.

Apparently, formal control theory cannot be efficiently applied in complex networks since most optimal control techniques suffer from severe limitations as they cannot handle systems of very high dimension and with a large number of inputs and outputs, further exacerbated when non-linearities are considered. It is also infeasible to control these networks with centralized schemes (the typical outcome of most optimal control design techniques) as these require high levels of connectivity, impose a substantial computational burden, and are typically more sensitive to failures, attacks, and modeling errors than decentralized schemes.

The decentralization of decisions is often recommended in the design of complex networks, and the decomposition and coordination of decisions are a great challenge. The mechanisms behind this network of decentralized design decisions create difficult management and coordination issues. Standard techniques to modeling and solving decentralized design problems typically fail to understand the underlying dynamics of the decentralized processes and therefore result in sub-optimal solutions. From this angle, it remains crucial to understand the mechanisms and dynamics behind a decentralized set of decisions within a complex design process. Towards this direction, the structure as well as the evolution of the network should be exploited for the development of successful optimal control techniques.

4) ENGINEERING SELF-ORGANISATION AND EMERGENT BEHAVIOUR IN COMPLEX NETWORKS

'Self Organisation' and 'Emergent properties' represent one of the most significant challenges for the engineering of complex systems [98], [99]. As outlined earlier, emergent properties can be thought of as unexpected behaviors that stem from interaction between the components of an application and their environment. In some contexts, they can be beneficial, but they can also be harmful if they undermine important operational and safety requirements [100].

A novel goal in any system is to strive toward engineering proven self-organisation and emergent behaviour. However, this is an area still in its infancy, and perhaps disputed [98], [99], whereby the dichotomy between the following two approaches does not help: i) On the complex systems side one 'lets' systems be and ultimately 'hopes' to display adaptation, self-organization and emergence — for example no one designed the internet or the transportation network; ii) But on the control engineering side the complex systems approach is an omen, as an engineer would question how one can let the system be, without any designed and proven properties in terms of stability, convergence, optimality and consistency of operation? Their primary difference stems from the fact that systems designed through classical control engineering processes are expected to perform foreseeable tasks in a bounded environment, whereas complex systems, either natural (living organisms, insect colonies, ecosystems) or large-scale man-made (communication networks, transportation networks, cities, societies, markets, multinational corporations) are expected to function in complex, open environments with unforeseeable contingencies, and thus require high adaptability so systems can evolve novel configurations emerging from organising their components in new ways. Whatever the case, adopting the emergent and self-organisation engineering paradigm in 6G can open perspectives on how strategies that mimic adaptation of highly evolved systems can be developed with simple rules/agents, leading to fundamentally and continually adapting and evolving networks.

However, as in many other man-made systems, engineering these properties at the outset is not realistic. In the real world, 6G networks are being designed and build in a linear evolutionary manner, with multiple decision points and ideas 'evolving' before an operational design 'emerges', driven by the many actors involved, such as the standards bodies, telecom equipment manufacturers, telecom operators, etc. Even so, there are still opportunities one can seek in aspects of 5G/6G to engineer self-organisation and emergent properties at design time, e.g. by incorporating specific features with positive and negative feedback, that will be useful for engineering the local interactions [98], [101]. Ultimately, with 'proven' self-organisation and emergent properties, whenever there are environmental changes the network can spontaneously and without external control evolve and re-organise, and hence strive toward predictable control and performance. It is worth noting that self-organization in networks has been identified by the 3rd Generation Partnership Project (3GPP) as one of the key concepts to reduce the operating cost associated with the management of a large number of nodes, albeit in a less ambitious form from what is described above [102].

C. MODELING PATTERN FORMATION IN COMPLEX NETWORKS

Complex systems consist of multiple elements which are arbitrarily interconnected and interact with each other as well as with their environment in unpredictable and unplanned ways. From this mass of interactions patterns emerge as a result of negative and positive non-linear feedback mechanisms acting at different spatiotemporal scales. Even though the interactions may be simple, the behavior of the whole system can be quite complex. Similarly, a network consists of nodes which are interconnected through arbitrary links

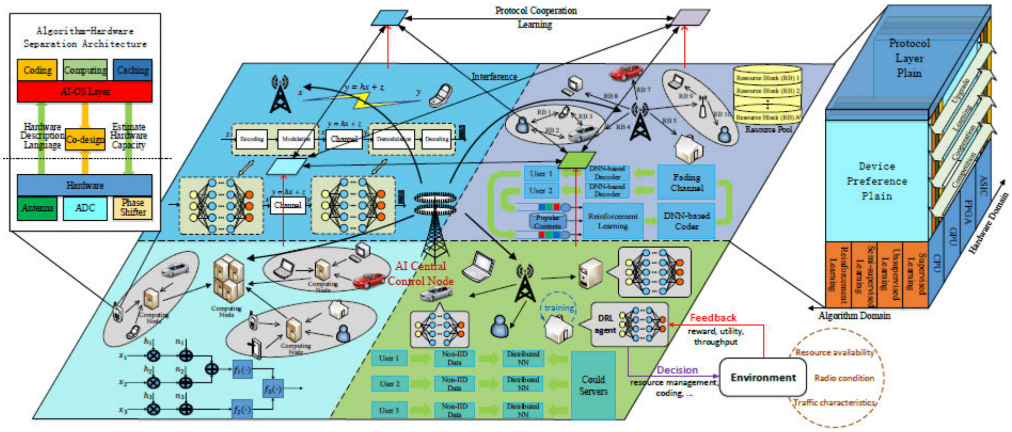


FIGURE 11. 6G cell architecture [103].

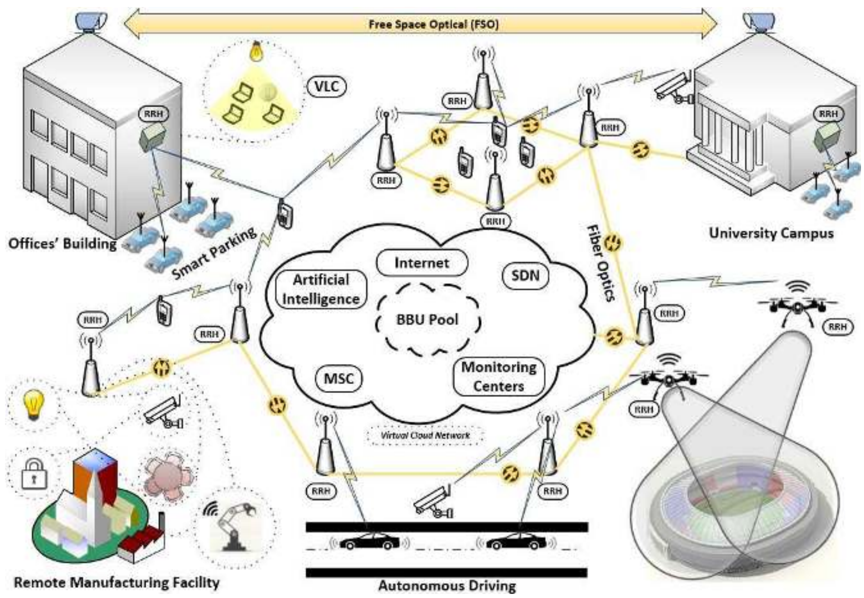


FIGURE 12. 6G cell less architecture [104].

and interact with each other in unpredictable and unplanned ways, using rules imposed by various protocols. From this point of view, complex systems seem to provide a theoretical framework for the study of the robustness and stability in real communication networks under perturbations, based on self-organized and decentralized operation. The way the patterns are formed and evolve within a complex environment can be investigated and the inherent complex mechanisms that provoke this behavior will provide the basis on which robust networking approaches can be developed.

The study and the modeling of pattern formations in existing communication networks should involve some basic steps. Initially, the identification of sub-units and interactions involved in a collective process can be carried out through observations and experiments in the complex system's environment. Then, a hypothesis formation (simulation and/or modeling) should be developed and its correctness based on its capability to cope with system's perturbations should be carefully tested. In other words, by changing the rules or parameters of the system in a controlled manner, it should be determined whether the outcome matches that was predicted by the hypothesis (simulation/model).

VII. WAY FOR COMPLEX NETWORK ANALYSIS OF 5G/6G NETWORKS

Based on the analysis above and bearing in mind the future of 6G as presented in several research works so far, it is far from obvious how the complex analysis of the 6G networks will depend on the network architecture or architectures that will prevail. Two prominent architectures are the cellular architecture (Fig. 11) that already exists in mobile communication networks or the cell- less architecture (Fig. 12) that is being promoted as a new concept in 6G networks.

For the first case (cellular architecture), as in the topology suggested in Fig. 11, a Power Law characterization would be more suitable to describe the network. In this case central cellular antennas and the mini-cell antennas can be considered as high-degree nodes which are disproportionately attractive (large degree), acting as hubs. These nodes are robust to random node failures, but extremely fragile to the failure of a hub which essentially disconnects the network. In the second case (cell- less architecture), as in the topology of Fig. 12 which implies that all nodes are equivalent in terms of degree (networks with Poissonian degree distributions) the network is not robust to random failures, however it is not vulnerable to targeted attacks on the hubs (as there are no hubs in them). Thus, besides information dissemination (e.g., hubs reaching a large portion of the network) degree distribution is also very important for the percolation/connectivity properties of the network.

Another important parameter that needs to be considered in 6G networks, is the average distance or diameter. 6G topologies are expected to have ''small-world'' properties as the connections are not deterministic/ordered, as for example in a chain or a grid where ''small- world'' properties are not expected. In random networks (Poissonian/Erdos-Renyi) the diameter (longest shortest path) is proportional to $\ln N$ where N is the size of the network. This small ''worldness'' is due to randomness in the connections that create shortcuts in the network. Power- law (or scale-free) networks are also small-world networks if the power law exponent is $\gamma > 3$ and ultra-small worlds [diameter growing as $\ln(\ln N)$] if the power-law exponent is $2 < \gamma < 3$. Clearly, small-worldness is important for efficient navigation/routing [105].

Moreover, clustering, or triangles in the network, i.e., the probability that two neighbors of a random node are themselves connected is an important feature that is expected to appear in 6G networks. In 6G networks nodes (e.g. Device-to-Device and UE-Based Virtual Base Stations [68]) are expected to be deployed on a wide geographic space and communicate if they are within transmission range to facilitate BS offloading. Strong clustering is also important for information propagation as it provides path diversity in the network, e.g., if some links go off/fail bypasses can be found. On a tree topology for example (has zero clustering) there are no bypasses and as a result if a link fails the topology gets disconnected.

Blockchain technology is also envisioned to play a central role in the management of the massive data that are expected to be created and handled in 6G communication networks. The authors in [106] show that the Ethereum network, being a platform used for human interactions, can also be described and modeled using a network theory approach. According to their work, the degree distribution of this type of networks, often displays a power law distribution. This phenomenon can also be observed when constructing a network that represents Ethereum transactions between wallets. In this case each wallet is a vertex and a transaction between two wallets is an edge. Adopting a similar concept, the authors in [107] propose a random graph model for performance modeling and analysis of the inventory-based protocol for block dissemination. The proposed model addresses the impact of key blockchain parameters on the overall Bitcoin performance. The overlay Bitcoin network is modeled using an Erdos-Renyi model to generate connected random graphs.

Programmable Wireless Environments enabled by Hyper-Surfaces and Intelligent Surfaces [30], [32] are also expected to play a central role in the unpredictable wireless environment [16], especially at combating the distance problem [108]. Programmable Wireless Environments result from the mass deployment of HyperSurface units within a space, enabling (i) complete, software-defined control over the wireless propagation phenomenon within HyperSurface-coated environments, and (ii) the interplay with existing software services and networking equipment. Pivotal studies has shown that these traits can yield impressive gains in wirelesss communication efficiency, interference mitigation, physical-layer security and wireless power transfer [16]. Recently real time dynamic control of HSFs was proposed [109], which is especially appealing for moving networks.

Further to the above, due to the diversity of nodes/connections that are expected in 6G networks, modern temporal network theory [110] could be a useful tool for modeling them. In this theory attributes beyond simple nodes and links as in classical graph theory, are included. Introducing information about times of interactions can make predictions and mechanistic understanding more accurate.

Further, as indicated in Section V, user and intermediary node mobility and miniaturization have been pivotal in driving a paradigm shift in the Internet towards a flat, software first implementation, promoting adaptivity and re-configurability, rendering it dynamic in nature. This dynamic nature paves the way for the adoption and development of alternative mathematical tools [69], [76], for the analysis of complex systems deviating from traditional approaches. In particular, the fields of **Temporal Networks (graphs)** [72], [73], **Dynamic Network Analysis** [74] and **Evolutionary Graph Theory** [75] which have appeared in different contexts are highly relevant to the current ''dynamic'' Internet. Temporal Networks can be crudely considered as time varying networks where the graph links appear and disappear at specific time instants generating a sequence of graph representations over the same set of nodes. This time variance generates important properties relative to static graphs nicely reviewed in [73]. In addition, Evolutionary Graph Theory aims at exploring how the underlying topology affects the evolution of population in a setting where individuals occupy vertices and edges characterized by weights which represent reproductive rates. The aforementioned tools are coupled to the dynamic nature of the network. This dynamic nature stems from node mobility which often necessitates the need for re-configurability and adaptivity. Re-configurability is harnessed by novel enabling technologies expected to be pivotal in future 6G design at different layers as for example software defined networking at the network layer and phased antenna arrays and meta-surfaces at the physical layer. The prospect of exerting programmatic control over all aspects of impinging electromagnetic waves on a metasurfaces, as recently realized in [29], [111], paves the way for real time configuration of the physical layer properties, redefining even the fundamental communications laws, realizing extraordinary applications such as Programmable Wireless Environments [16]. Moreover, these tools may prove to be handy in analysing 6G challenges pertinent to information flow. Advanced hardware capabilities, have led to radical advances in computational intelligence with extraordinary applications in critical infrastructures such as the smart grid and intelligent transportation. These, have in turn increased the security threats in both their intensity, impact and significance, something which is expected to be even more vivid in 6G deployments. Graph theoretic tools and networks theory have been used extensively in theoretical biology to investigate the spread of diseases in networks [112], [113] and can thus be used to analyse and combat cyberattacks which to some extent show similar behaviour [114]. Moreover, they may prove a useful tool in analysing information flow for machine learning/artificial intelligence applications within the network, characterizing their effectiveness. Network monitoring, in many cases feeding machine learning techniques have been realized by technologies such as Deep Packet Inspection, and due to the dynamic resource allocation and orchestration often facilitated by SDNs/NFVs, dynamic information flow characterization is crucial in determining the effectiveness of the proposed methods.

It is a fact, that the issue of complexity is also critical in future 6G Networks and a major issue is to facilitate complex systems methodologies to harness the difficulties associated with the underlying complexity. Towards this end, recent work [115] has indicated the potential of machine learning and artificial intelligence methods to be used for prediction purposes thus harnessing the often chaotic system behaviour from a dynamical systems perspective. In addition, the idea of system degeneracy, with reference to structurally different functional topologies having functionally identical properties has been exploited in [42], [116] to enhance distributed computation. The latter reveals how structure arising in complex systems at different scales can be exploited for resource optimization thus paving the way for similar explorations in different contexts and applications.

The above discussion illustrates that the adoption of complex theory is essential in the design and modeling of the new mobile networks and especially in the heterogeneous 5G/6G mobile communication networks, and this should be done from the outset. An exemplary approach appears in [42], [117], where the communication network itself is treated as a complex system. The focus of their study is the organizational structure of communication networks that affects the execution of network functions by studying their complexity, degeneracy and the principles of emergence. Within this framework they introduce the functional complexity metric and show that it has high correlation with network metrics, thus enabling the design of network aspects related to those metrics before the network is operational. A factor which can hinder the adoption of complex systems theory by the communication networking world is the plethora of proposed complexity metrics is an area where confusion often arises. Being a multidisciplinary field with often separate developments, a large number of metrics were defined by researchers from their own perspective to characterize complexity. Indicatively, Loyd [118] in his 2001 article 'Measures of Complexity: A Nonexhaustive List', lists over 40 metrics, including centrality (betweeness centrality, eigenvector centrality, etc..), node degree, average path length, emergence, degeneracy, clustering coefficient, functional complexity, excess entropy, neural complexity, and matching complexity, which he classifies into 3 broad categorizations. However, beyond a mere classification, we argue that for communication networks we need to define and more tightly link the complexity metrics with commonly adopted communication networking metrics, thus opening up the complex systems theory to the wider 5G/6G researchers.

As a final remark, new network designs as for example the 5G/6G and the Internet of Things (IoT), should adopt the principles of complex networks from the outset. A concerted socialisation effort is required to convince all actors of the utility of this approach, and this is where the various research funding and standards bodies can take a leading role.

VIII. CONCLUSIONS

In this paper we present basic concepts and properties exhibited in complex adaptive systems and discuss the most important network modeling paradigms that emerged over the last few years. Furthermore, we present communication networks from the perspective of complex systems. Previous research efforts by Erdos and Renyi, Watts and Strogatz, Barabasi and Albert, Carlson and Doyle as well as more recent works like those of Dmitri Krioukov, Fragkiskos Papadopoulos et al, popularized the idea that networks form randomly into a direction of organization and hidden order. The characteristics of random networks, small-world networks and scale-free networks can be observed in many levels of different disciplines. This dictate an imperative need to develop a new theoretical framework to help explain the complex and unpredictable behaviors of communication networks and design alternative network protocols which are provably effective and robust. Such a framework can serve as a starting point to develop a unified theory for complex systems, useful in explaining how the interaction between the individual components of such systems allows the emergence of a global behavior that would not be anticipated from the behavior of components in isolation. Modeling of complex communication networks like 5G or 6G can benefit from complex analysis including modern approaches on the subject like the works presented in [77] and [117] on the Hyberbolic Geometry of Complex Networks, as well as the modern temporal network theory [69], [110]. We are also confident that the complexity, the diversity and the heterogeneity of 6G Wireless Communication Networks will lead in the researching of revolutionary theories in order to accurately model them. As a final concluding remark, we urge the complex theory and networking communities to come together and collaborate toward the evolution of the new and continuously challenging networks of 5G and beyond. It is clear from the above discussion that a concerted socialisation effort is required to convince all actors of the utility of this approach, and furthermore, this is an area where the various research funding and standards bodies can take a leading role.

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