Complexity for edge intelligence in 6G

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Abstract

It is envisioned that 6G networks will be more a revolution than an evolution in comparison with the previous generations, as it will represent a fully connected and intelligent network, where heterogeneous interconnected elements are able to dynamically interact with each other in an unplanned manner, commingling into a complex ecosystem. Wireless networks are growing in size and in deployment density, demanding scalability and adaptability to be part of the future network design. Furthermore, the trend is to transform networks' architecture and service implementation. The former is shifting from a traditionally rigid and hierarchical - hardware first - to a more flat and flexible- software first – implementation, enabling, among other things, dynamic resource sharing and on-demand resource allocation. The latter is related to new services and use cases with strict requirements (e.g. latency, throughput, reliability), dynamically demanding resources on a more fine-grained level. Very heterogeneous devices and kind of networks, such as cellular, Wi-Fi, vehicular and Internet of Things (IoT), cannot be considered in isolation but belonging to the same ecosystem and are interdependent, constituting subsets of a network that evolve over time in accordance with user deployed infrastructure. Network will be not only a pipeline for transferring information from a source to a destination, but must be modelled, analysed, and designed as a living organism, which evolves over time and adapts to the changes in its environment, acting in a cognitive way. To support high performances, new functions, services and to satisfy the stringent requirement of the typical 6G applications, a key pillar aspect is the shifting of the intelligence at the edge. It means bringing some AI features to each end node, or on clusters of nodes, so that they can learn progressively and share what they learn with other edge nodes to provide, collectively, new added value or optimized services. Within mobile networks, this is handled by Multi Access Edge Computing (MEC) infrastructures that are expected to be incorporated into future 6G networks, creating the so-called distributed and collective edge intelligence. Edge devices become intelligent hubs able to deliver highly personalized services directly from the edge of the network, enabling applications to perform at their best. Considering that the edge is populated by humans and that end devices are often hand-held ore wearable, the social aspect and human dynamics are even more central in the design of such networks. Also, to enable a paradigm in which people are not only mere users of the

applications and adapt to the technology but vice versa.
Starting from these premises, in this dissertation, it is proposed a complex perspective to enable the deployment of edge intelligence in order to design innovative ICT 6G applications. The proposed and applied methodology is interdisciplinary and bio-inspired and based on tools belonging to several research fields: the theory of complex systems, the Evolutionary Game Theory, Multiplex and Temporal Multiplex Networks, and the Epidemics Modelling. This methodology is the most suited to include all the dynamical and complex features of the future 6G networks, taking into account aspects, which are becoming even more crucial, as the evolutionary dynamics, the emergent behaviours, the cooperation, the multiple interactions and their interdependence, the heterogeneity and the social and human-related aspects. The research topics of interest during the PhD period can be summarized in the following research questions which guide the development of this thesis:

- What are the most suited tools and methodology to quantify the impact that micro-scale structures and dynamic properties have on macro-scale performance? In what terms is it possible to represent a 6G network as a complex system?
- What is the most appropriate approach to measure, evaluate and characterize services and components in 6G networks?
- Is it possible to quantify the impact of human behaviour and dynamics in designing, providing and evaluation of ICT services in a 6G scenario?
- How can edge nodes trigger cognitive and distributed decision mechanisms, adapting themselves and learning from the environment? How can they tune their dynamics in order to construct the connected and distributed intelligence, optimizing the use of available resources and improving the QoS?

After a discussion about the evolution of communication networks, from 1G towards 6G, and the need for new approaches to analysis, modeling and design; the literature related the methodology and tools is reviewed. Then, through the chapters of the thesis, the research questions are answered, showing both analytical and data-driven models, including new parameters and measures able to capture, measures and combine the dynamical and complex aspects of 6G networks, considering QoS, QoE and human-related aspects. Simulations results are shown and discussed. Finally, the conclusions summarizes the research contributions and indicates possible future developments.

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Chapter 1

Introduction

1.1 Complexity for Edge Intelligence in 6G: An Overview

The outbreak of the COVID-19 pandemic has highlighted the crucial role embodied by networks and digital infrastructure in keeping society running and people connected. It has brought out, perhaps as never before, the pivotal importance of existing applications and services such as remote working and online education and the need to invest in developing ones like driverless vehicles, remote surgeon, unmanned delivery, smart healthcare, and autonomous manufacturing [56]. On the basis of these premises, investments that countries will make in research and development of telecommunications of sixth-generation (6G), in the Internet of the Future with its infrastructures and services, will be the starting point for the development of entire sectors of the society [3].

It is envisioned that 6G networks will be more a revolution than an evolution in comparison with the previous generations, as it will represent a fully connected and intelligent network, where heterogeneous interconnected elements are able to dynamically interact with each other in an unplanned manner, commingling into a complex ecosystem [126], [119]. .

These networks will be engineered providing distributed intelligence techniques to various and heterogeneous end nodes, enabling them to quickly adapt to new conditions in the network and in the environment [139]. Network adaptation, resilience, and self-driving with zero manual intervention will be key pillar aspects and it will be crucial finding a trade-off among several factors such as capacity, power consumption, latency, complexity rescuing in such a distributed collective intelligence in the context of multi-agent collaborative network management [143].

For these reasons, in contrast with the previous telecommunication networks 6G networks will present evolutionary tendency such as scaling, adaptation, resilience, self-driving structure and flexibility. To begin with scaling the network will be associated with a tremendous network size including all kinds of entities, ranging from simple sensors to sophisticated devices, and including different network scenarios as cellular, vehicular, Wi-Fi, Internet of Things (IoT) systems, with different service capabilities and requirements. Furthermore, interactions among these entities will be heterogeneous and result in a diverse variety of traffic.

Next, future wireless networks will tend to have a self-configuring architecture, where each entity cooperate with others to complete tasks, giving to the network the characteristic of "being ad hoc". In addition, the mobility of entities results in a complex time-variant network structure, which requires dynamic time-space association.

Last but not least, considering that the network's edges, even now, are populated by hand-held mobile devices, it becomes pivotal taking into account [100] human beings themselves with their devices (from wearable to hand-held) and, consequently, their behaviours are active elements of the network, forming a sort of heterogeneous and aggregated things, playing an active role in the technical aspects and in the design of the networking functions, representing the interacting part that coexist in what can be considered as a complex socio-technical ecosystem. With the proliferation of these hand-held mobile devices, is increasing also the demand for a high quality of service (QoS) and quality of experience (QoE), so future wireless networks have to support a broad range of compelling applications, with high-rate, low-latency, low-cost and reliable information services.

In addition to these aspects, the typical and fundamental operations of these networks with denser deployments, more base stations, countless users, as well as with new technologies which are expected to be introduced in 6G networks (e.g. the Artificial Intelligence (AI), Machine Learning (ML), Terahertz (THz) band communications) are further enhanced by the trend toward softwarisation of networking functionalities. In other words, the network architecture is shifting from a rigid and hierarchical implementation to a flat and flexible one, leading some parts of the network architecture, traditionally static (such as base stations) to evolve towards a more dynamic implementation where the intelligence and functionalities are pushed at the edge.

The forth-coming generation of communication networks should be considered not only as a simple pipelines for transferring information from a source to the destination, but also as a source of information and data (e.g. sensor networks collect information about the environment, vehicular networks provide information about the traffic), and able to store, communicate, process and extract further knowledge from them.

The increase demand for resources precipitates the need for cooperation and collaboration such that those networks cannot be considered individually but as a part of a bigger and complex ecosystem. The network will act as a living organism which is able to evolve, time by time, to the changes in its environment and 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 dynamically changing manner to meet applications' demands.

The network architecture will be user-centric and with end nodes more central than ever and playing a key role in content diffusion, learning, computation and organization. In this perspective, one of the revolutionary concepts for 6G networks is envisioned to be the shifting from the concept of "connected things" or Internet of Things (IoT) or Internet from Everything to the so-called "connected intelligence" which inevitably revamp fundamental network concepts, increase the network's complexity and makes Edge Intelligence (EI) at node level one of the key enabling factors [111].

In this respect, one definition of particular importance for 6G is represented by the Multi-access Edge Computing (MEC), initiative within ETSI, [54], which acts as an enabling technology for 6G. In this architecture, edge intelligence refers to data analysis, development of solutions and intelligent services and functions deployed at the edge of networks where data are generated and further utilized in order to reduce latency, costs, and security risks.

All these aspects together with the innovation strictly related to the network architecture, which are moving from closed hierarchical or semi-hierarchical structures to open, distributed and networked ones, represents a driver for the application of new approaches able to analyse, model and design these systems.

The definition of complex system as "a system in which large networks of components with no central control and simple rules of operation give rise to complex collective behavior, sophisticated information processing, and adaptation via learning or evolution" [98], [31] is perfectly aligned with the vision of future mobile networks and represent a useful and effective tool capable to model the behaviour of the forthcoming 6G telecommunication networks [126].

Complex systems theory [126] , by definition, takes into account methodologies and tools built to analyse emerging behaviours, cooperative and collaborative dynamics among a large interlacing number of elements, represented by nodes connected by relationships of different kind. These nodes adopt simple actions in a distributed manner, triggering complex system-wide patterns and behaviors; with appropriate design and management, the interaction of elements in this way enables aggregate capability far exceeding the capabilities of a single system's element.

Different sciences, physics, biology, mathematics, engineering and many others, are facing with the problem of increasing complexity, testifying the interdisciplinary nature of the complex system analysis. Even if tools such as information theory, game theory, network science, statistical mechanics, computational modeling, distributed optimization, are very suitable to study different system properties, none of them individually allows us to fully comprehend a complex system. Hence, the complexity sciences are more a revolution in methods than a theory, and the interdisciplinary is one of its characteristic aspect, for example [37]:

- Complexity metrics are based on information theory (e.g. mutual information, entropy). However, instead of modeling the amount of randomness in the system or the amount of information exchanged between two system entities, complexity metrics measure how much the behavior of system parts deviates from the behavior that is expected from a completely random or a linear system [31].

- Network science allows us to model highly complex systems by focusing on the modeling of interactions rather than on the individual parts and it provides a set of tools that are helpful to understand the interdependence among the system entities. In addition, the increasing interest for the complex systems theory and the advancements of the recent years have showed that, in order to shed light on the complexity of the large variety of real systems, the description in terms of single network is an oversimplification, which represent a loss of information and is not able to capture the network's dynamics and patterns deriving from the simultaneous interactions of more than just one network. On the contrary, multilayer networks distinguish different kinds and channels of interactions between nodes through different layers. Nodes in the network are linked to each other via multiple edges, revealing important information about connectivity and complexity [24, 29].

- Complex systems rely on distributed decision making, which can be studied thanks to game theory mathematical tool. Due to the heterogeneous set of agents and rules of interaction between them it is usually impossible to describe the system with a set of selfish agents or closed form equations. Unlike game theory approaches that rely on strategic interactions between rational decision-makers, individual agents within a complex system often exhibit a behavior that would not be categorized as rational, and therefore the decision making process is not always based on the maximization of the mathematical expectation of the cost function. To evaluate emerging dynamics from the interactions in complex networks it is useful to introduce the Evolutionary Game Theory mathematical framework which is applied to several fields such as economy, biology, computer science, communication networks, security, power control issues in wireless scenarios, distributed systems (e.g. peer-to-peer networks), artificial intelligence and all those situations where elementary units (or agents) have to coordinate their actions to achieve a common good, as the individual strategical decisions and behaviours affect the outcomes of others in the same environment [103, 113].

- Statistical mechanics tools allow us to study systems that are composed of a big number of entities, in which the system behavior often depends on the chronology of interactions rather then the current states of the individual elements. For this reason network theory allows us to add another dimension of analysis, the time, considering temporal networks rather then the time aggregated structure [72]. This is particular relevant for some collective processes on top of them, such as co-evolving spreading, diffusion phenomena, content dissemination or social contagion, for which it is useful to resort to the classical epidemiological modes thoroughly used in network science for social behavioural analysis, misinformation diffusion, infectious disease and emotions spreading, which spread inter-personally like a virus [110, 124, 122].
- The huge amount of heterogeneous data generated by the devices disseminated in the world, but also the online social platforms or the collection of event logs are means through which reach the so-called cyber physical convergence. The application of techniques from data analytics, infodemics [91], data mining, or sentiment analysis allow us to retrieve such a knowledge; these data represent digital fingerprints from which extract the behavioural pattern of humans, the topics which polarize their attention, their degree of awareness. All these information are crucial in order to analyse empirically the dynamics of the complex systems, also rescuing on data about virtual interactions and physical ones in proximity networks [58].

1.2 Research Questions

This Ph.D. dissertation addresses some main research questions:

- The future 6G communication networks represent more a revolution than an evolution of previous technologies, constituting a complex ecosystem of things and people. This makes it necessary to introduce new approaches and tools able to take into account new and complex aspects such as emergent dynamics, competition and cooperation, collective behaviours, and interdependence. It becomes crucial understanding how the local interaction rules lead to global organization/synchronization, correlating them with certain network Key Performance Indicators (KPIs).
  What are the most suited tools and methodology to quantify the impact that micro-scale structures and dynamic properties have on macro-scale performance? In what terms is it possible to represent a 6G network as a complex system?

- The upcoming 6G has the ambition to introduce heterogeneous interconnected elements, dynamically interacting with each other as well as with their environment in an unpredictable and unplanned way. A key pillar concept is pushing the intelligence at the edge, by assigning a a key role to edge nodes in content diffusion, learning, computation and organization. The traditional attributes applied to measure and characterize communication networks such as interference, coverage, throughput, robustness and costs are not able to describe dynamics and crucial aspects of future wireless and mobile networks. It therefore becomes necessary to have innovative tools and approaches to assess the QoS and characterise the nodes of a 6G network, taking into account new, dynamic and cognitive aspects.
  What is the most appropriate approach to measure, evaluate and characterize services and components in 6G networks?

- Human beings with their behaviors and social dynamics become increasingly central in 6G networks. Not only because the edges of the network are populated by humans and their devices, hand-held or wearable ones, but also because the idea that is spreading is that people do not have to adapt to the technology but vice versa. In this way, human beings and factors become an integral part of the network architecture and not just mere users.
  Is it possible to quantify the impact of human behaviour and dynamics in designing, providing and evaluation of ICT services in a 6G scenario?

- Multi Access Edge Computing (MEC) infrastructures, moving the intelligence from the central cloud to edge computing resources, are expected to be incorporated into future 6G networks and are a key pivotal point for the so-called distributed and collective edge intelligence. Edge devices become intelligent hubs able to deliver highly personalized services directly from the edge of the network, enabling applications to perform at their best. The idea is to bring some AI features to each node, as well as on clusters of nodes, so that they can learn progressively and possibly share what they learn with other similar (edge) nodes to provide, collectively, new added value services or optimized services.
  How can edge nodes trigger cognitive and distributed decision mechanisms, adapting themselves and learning from the environment? How can they tune their dynamics in order to construct the connected and distributed intelligence, optimizing the use of available resources and improving the QoS?

1.3 Methodology

During my PhD period I had the possibility to focus my research methodology on an interdisciplinary approach, this aspect represented a great opportunity for me because it represented the possibility of combining fields that I thought were disconnected and belonging to different research subjects. This allowed me to change my approach to research topics I faced, seeing them not as individual ones but as different aspects of a unique most complex and bigger research area.
I started my Ph.D. in Systems, Energetic, Computer and Telecommunications Engineering driven by the interest and the desire to learn more about the issues and the methodology I came across during my MSc thesis period. On that time, I focused on the evolutionary dynamics of collective behaviours through the Evolutionary Game Theory in a complex social network modelled as a multiplex network.
It was fascinating for me considering that biological systems are an inspiration for the research concerning ICT development. In fact, the real world is the first example of enormous, dynamical, heterogeneous and complex system where its organisms are able to survive, self-organise, adapt, cooperate and evolve in a such complex environment, exploiting their context-awareness, without a centralized control. Similarly communication networks are becoming even more heterogeneous, dense and interconnected and the tendency is to design them in a robust, adaptive and scalable way. The bio-inspired approach, applied to ICT, gives the opportunity to use innovative algorithms, tools and analytical models to optimise and improve the design and management of ICT, investing new fields such as context-awareness, social networking, multilayer networks, evolutionary game theory, content dissemination, smart mobility, smart healthcare, dynamic complex systems, smart platforms and services.
In particular, it was intriguing evaluating how microscopic interactions of simple self-organised agents and their relationships have an impact on the the emergence of a collective intelligence (for instance imitating the collective behaviours of bees and ants, e.g. swarm intelligence) leading towards a common good for the whole system. Particularly interesting is noting that interactions among elements are not trivial and follow recurrent and complex patterns and that the individual interacting entities are themselves heterogeneous and complex (e.g. human beings in social networks or nodes of future telecommunication networks). To better understand these complex dynamics I have focused on the mathematical framework of Evolutionary Game Theory, able to capture the underlying mechanisms and the hidden dynamics of systems and shedding light on how and why some behaviours emerge following a specific pattern (e.g. cooperation and competition). To deal with the complexity of social interactions, I explored the paradigm of multilayer networks, since the presence of nodes in multiple layers of a system is the key to understand emergent phenomena, adding an

extra dimension of analysis and displaying what is the role both of intralayer interactions, as in monoplex representations, and of interlayer interactions. To disclose the complexity in co-evolving and interdependent spreading processes, to analyse the phenomenon of social contagion and the key role that ties have in diffusion phenomena I included the tool of epidemiological models which find application in network science, social behavioural analysis, content diffusion, infectious disease and emotions spreading.
My PhD research project is focused on the analysis and modelling of complex networks, processes and dynamics allowing the design of innovative ICT services based on collective cooperation, competition, social contagion dynamics and their interdependence. To deepen my knowledge about the state of the art, I searched, studied and evaluated numerous scientific contributions of related works with the aim to find new approaches, new methodologies to develop analysis model, tools and frameworks suitable for different areas of interest to me.
In this thesis the smart city and smart healthcare applications scenarios are considered, because they represent two of the most challenging scenarios, due to their stringent constraints. The applied methodology represent a tool to improve the urban planning through a cognitive perspective of the city as Internet of People and Things, analysing it as a complex relational system. This approach enables an understanding of how the dynamical changes on the structural heterogeneity within a city can have an impact on innovative sectors which have been actively engaged in finding solutions for sophisticated and innovative services. In this field, for instance, crowdsensing-based applications are becoming increasingly widespread. In this kind of applications the evaluation of human-related aspects are crucial, in fact, human behaviour directly affects the quality of the provided final service. In the course of reading this thesis you will see that the proposed approach makes it possible to define innovative QoE evaluation policies based on the amount of information shared and on quality, including aspects such as the social honesty. It will be considered a vehicular traffic monitoring crowdsensing application, rethoughting the design of incentive mechanisms through a game-theoretic methodology. Experimental results, will demonstrate that the proposed methodology, based on both quality and quantity of reports and the local or microscopic spatio-temporal distribution of behaviours, is able to better discriminate users' behaviours. This multi-scale characterisation of users (both macroscale and microscale) represents a novel research direction and paves the way for novel policies on mobile crowdsensing systems. To give another example, in this thesis, it is proposed an understanding of the interplay between the collective attention dynamics and the two co-evolving spreading processes as awareness and epidemics, in consequence of the occurrence of an extraordinary event as the ongoing COVID-19 epidemics. The findings demonstrate how the proposed modelling and data-driven procedures, represent a complex digital observatory to detect a social network

marker exploiting the digital traces of behaviours and connections of people. Thanks to the proposed approach, it is possible to identify the dynamical collective patterns, social networks markers to optimally schedule timely crisis response planning. This can improve the future preparedness plans, risk factors assessment and actionable strategies for delaying or stopping the spreading. This can offer more insights on human behaviours and interests leading to an optimally management of the dissemination and the discrimination of the contents, by including mechanisms to improve users' cognitive ability. A possible implication for the future can be an increasing of discriminating capacity for users to identify better information in comparison with low-quality ones or misinformation.

Below, I sum up the issues of interest that I studied in that period and I am going to go in the next future. The following list of keywords represents also the macro areas of this dissertation:

- 6G Mobile Telecommunication Networks
- Multilayer and Multiplex Networks
- Social Network Analysis
- Epidemic Spreading Modeling
- Data Science
- Emerging Behaviors
- Evolutionary Game Theory
- Collective dynamics in social network
- Complex Systems and Networks
- Multi Access Edge Computing (MEC)
- Intelligent Internet of Intelligent Things
- Internet of People

In Fig. 1.1 it is summarized the mindmap followed during the PhD period, in order to faced with the different research topics but also to organize this dissertation.

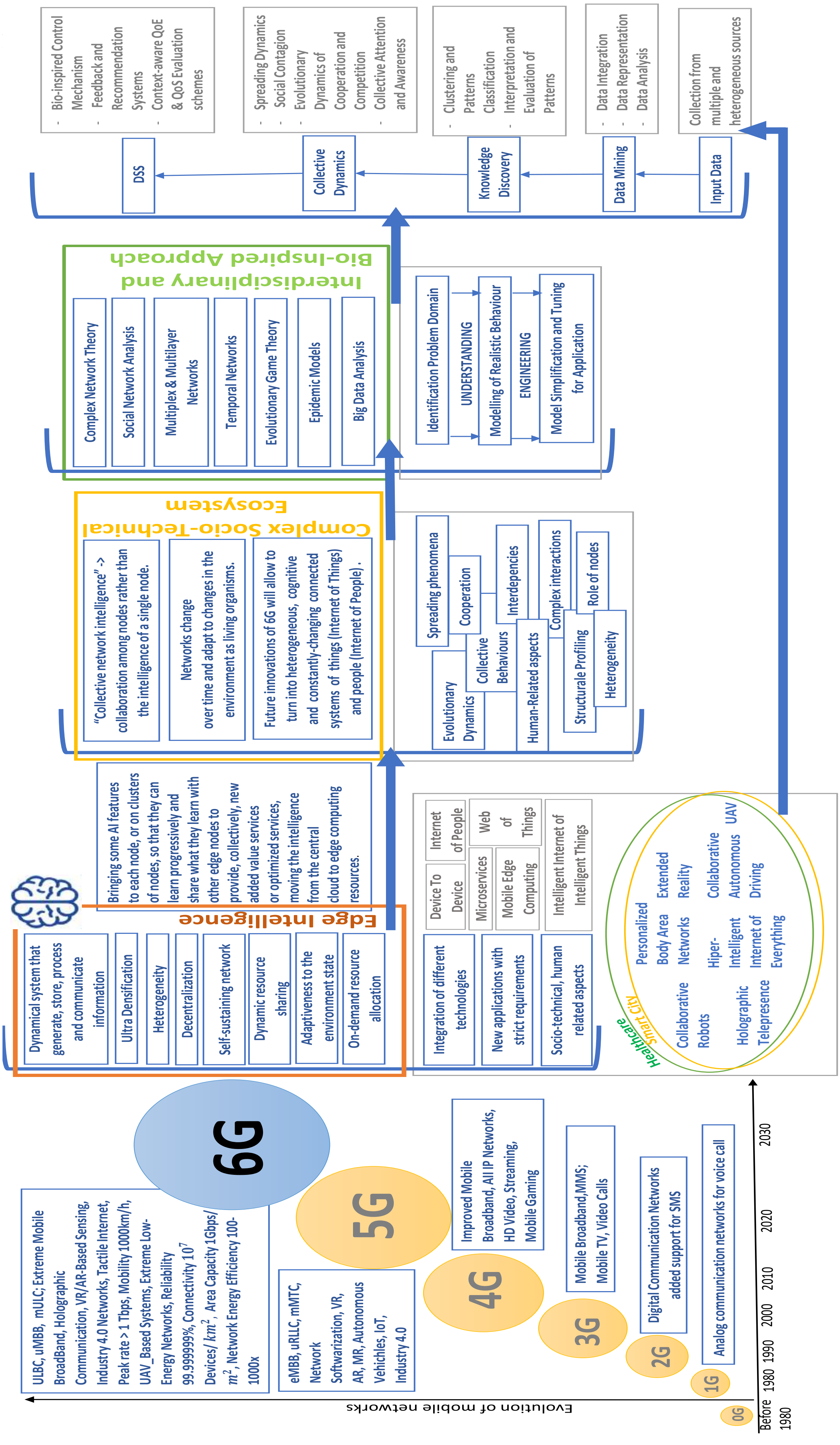

Fig. 1.1 MindMap of Keywords.

1.4 Dissertation Outline

The structure of this Ph.D. dissertation is as follows:

- **Chapter 2** summarizes the technological evolution from the 1G networks to the 6G networks, showing the main features and challenges posed by 6G. Particular relevance is given to the concept of edge intelligence, which is one of the key pillar concept of the next generation of communication networks. The second part of the chapter introduces the complex system approach and reviews the main complex network models (Random Graphs, Scale-Free networks and Small-World networks) and their main features.

- **Chapter 3** reviews the main structural properties of multilayer networks, detailing more the multiplex networks and highlighting the motivations behind the transition from Single- to Multi-layer Networks. The chapter introduces also the temporal multiplex networks to shed light on the dynamics of creation and dissolution of links. All the measures and properties of those networks are listed (node's, layer, edge and mesoscale properties).

- In **Chapter 4** the main notions of classical game theory and the framework of Evolutionary Game Theory (EGT) are presented. Together with the definition of game, solutions, social dilemmas and replicator dynamics, the last part of the chapter is focused on the introduction of parameters impacting the emergence of cooperation in multiplex networks (such as homophily and critical mass).

- **Chapter 5** reviews the classic epidemics models, which are used to study the diffusion of virus, as well as the phenomenon of social contagion, the diffusion of information, beliefs, fake news, habits and behaviors. The second part of the chapter presents more realistic models that provide for the introduction of heterogeneity and also the co-evolution and interdependence of several phenomena on a multiplex network.

- **Chapter 6** presents a 6G node's profiling technique based on the multiplex network, analysis of the diffusion, the competition dynamics and the clustering techniques. The second part of the chapter proposes a complex and dynamical approach, consisting of several inter-operable levels and different networked attributes, to quantify the quality of microservices for Internet of Medical Things applications.

- **Chapter 7** introduces analytical and data-driven approaches to quantify the impact of human-related factors, as homophily and heterogeneity, behaviours and dynamics. The presented approaches aimed at designing new policies for user-centric crowdsensing applications and at identifying social predictive markers of awareness dynamics for timely crisis response planning in emergency situations.

- **Chapter 8** proposes modelling approaches based on complex network theory to design novel edge computing organizational aspects in 6G scenarios (smart city, smart health-care, Web of Things), through the introduction of the multiplex social and temporal networks, which allows us to consider proximity contacts and social aspects, and EGT.
- Finally, **Chapter 9** concludes this thesis by revisiting the research questions posed in section 1.2, and summing up the main contributions of this dissertation, other than highlighting some key aspects to be investigated in the future research.

1.5 Dissemination

In this section the publications disseminated during the PhD period are listed.

1.5.1 Journal Articles

- Di Stefano, A., Scatà, M., **Attanasio, B.**, La Corte, A., Lió, P., Das, S. K. (2020). A Novel Methodology for designing Policies in Mobile Crowdsensing Systems. Pervasive and Mobile Computing, 67, 101230.
- Scatá, M., **Attanasio, B.**, Aiosa, G. V., La Corte, A. (2020). The dynamical interplay of collective attention, awareness and epidemics spreading in the multiplex social networks during COVID-19. IEEE Access, 8, 189203-189223.
- **Attanasio, B.**, La Corte, A., Scatà, M. (2021). Evolutionary dynamics of MEC's organization in a 6G scenario through EGT and temporal multiplex social network. ICT Express, 7(2), 138-142.
- Aiosa, G. V., **Attanasio, B.**, La Corte, A., Scatá, M. (2021). CoKnowEMe: An Edge Evaluation Scheme for QoS of IoMT Microservices in 6G Scenario. Future Internet, 13(7), 177.
- Scatà, M., **Attanasio, B.**, La Corte, A. (2021). Cognitive Profiling of Nodes in 6G through Multiplex Social Network and Evolutionary Collective Dynamics. Future Internet, 13(5), 135.
- **Attanasio B.**, Mazayev A., Du Plessis S., Correia N. Cognitive Load Balancing Approach for 6G MEC Serving IoT Mashups. Mathematics. 10.1 (2022): 101.

- Scatà, M., **Attanasio, B.**, La Corte, A. Bringing Complexity in a D2D-MEC System with a Temporal Multiplex Social Network to monitor and control Co-evolving Spreading Dynamic. IEEE Journal on Selected Areas in Communications (**Submitted**).

1.5.2 Conferences

- **Attanasio, B.**, La Corte, A., Scatá, M. (2020, November). Syncing a Smart City within an Evolutionary Dynamical Cooperative Environment. In 2020 AEIT International Conference of Electrical and Electronic Technologies for Automotive (AEIT AUTOMOTIVE) (pp. 1-6). IEEE.

- Grimaldi, S., **Attanasio, B.**, La Corte, A. (2021). A novel approach for the design of context-aware services for social inclusion and education. Human Systems Management, 1-12.

1.5.3 Book Chapter

- **Attanasio, B.**, Di Stefano, A., La Corte, A., Scatá, M. (2021). Evolutionary Dynamics and Multiplexity for Mobile Edge Computing in a Healthcare Scenario. Data Science and Internet of Things: Research and Applications at the Intersection of DS and IoT, 21-41.

1.5.4 Other

- **Attanasio B.**, Di Stefano A., La Corte A., Scatà M. (2019). A modeling approach based on Multiplexity and EGT for resource sharing in Fog /Cloud Computing. International School on Data Science and IoT, Catania Italy.

Chapter 2

The Road towards 6G

Overview: The 6G has the ambition to provide new directions to deal with future network challenges. It will address the constraints and the performance requirements of innovative applications, with highly increasing resources demands, through innovative approaches [126]. Major challenges and limitations of fifth-generation (5G) mobile networks arise from scenarios such as smart healthcare and smart cities [105, 79, 147], whose applications have stringent constraints, particularly in terms of latency, data-rate, processing, availability, global coverage and connection density. In addition, 5G networks will not have the capacity to deliver a completely automated and intelligent network that provides everything as a service and a completely immersive experience [41]. The proliferation of incredibly heterogeneous devices, ranging from simple sensors to sophisticated ones and the different network scenarios as cellular, vehicular, Wi-Fi, Internet of Things (IoT) and Internet of Everything (IoE) systems, shapes a fully connected network of millions of people and billions of machines. In this context, edge intelligence [111, 143, 68] will be a key enabling factor for future networks in order to improve performances, functions and services. For this reason, it is a growing the interest for interdisciplinary complex system approach to support the analysis, the modelling and the design of 6G systems [41, 60, 126, 119, 5, 76]. This approach will be crucial in order to introduce a key enabler for edge intelligence, new technologies and network features.

2.1 Evolution of communication networks

During the last two decades the communication networks evolved from the first generation networks (1G) to the fifth generation (5G) by introducing a countless number of novel ideas aimed at meeting the stringent requirements set out [154]. The 1G analog cellular systems appeared in the United States and Europe around the year 1980. Since then, a new generation of mobile communications was introduced to market approximately every ten years. Around 1990 1G systems were replaced by the second generation (2G) of cellular networks and

the Global System for Mobile Communications (GSM) achieved a great success providing mobile voice, short texting, and low-rate data services. Later, around 2001, thanks to the innovation in technologies represented by Code-Division Multiple Access (CDMA) the third-generation (3G) (WCDMA, CDMA2000, and TD-SCDMA) was developed. This technology was able to support high-speed data access with a rate of several megabits per second. In 2009 the commercial Long Term Evolution (LTE) networks were launched constituting the fourth generation (4G) mobile broadband. The 4G networks was enhanced by innovative technologies such as multi-input multi-output (MIMO) and orthogonal frequency-division multiplexing (OFDM) leading to the proliferation of smart phones and fostering the mobile Internet industry. In the early 2019, we stepped into the era of 5G communication services which attracted, and are still attracting, an unprecedented attention from the whole society. 5G expands mobile communication services from human to things, and also from consumers to vertical industries, enabling a wide range of services from traditional mobile broadband to Industry 4.0, virtual reality (VR), Internet of Things (IoT), and automatic driving [76]. In particular, in 2020, the outbreak of the COVID-19 pandemic highlights the unique role of networks and digital infrastructure in keeping society running and people connected. The importance of services and applications, such as online education, remote working, driverless vehicles, remote surgeon, unmanned delivery, smart healthcare [105, 79], and autonomous manufacturing has rapidly become pivotal. For this reason we have seen the expansion of investments in the telecommunication field and the the proliferation of 5G in several countries across the world. [94, 2, 56, 83, 14, 1].
Right now, although 5G deployments is still on its way across the world (see Table 2.1), the attention of research and industry is shifting towards the 6G systems. In fact, in accordance with [3], in the coming years the development of entire sectors of the society will depend on the investments that countries will do in research and development of telecommunications infrastructures and services, from edge cloud to Internet of Things and in prospect of new network architecture towards 6G and the Internet of the future.
In this perspective, the main research topics will be focused on:

- open, disaggregated, software-based and programmable network architectures.
- the migration of distributed cloud functions, the transformation of the network into a computing platform based on open and programmable micro-services.
- the development of control algorithms and the optimization of the network based on artificial intelligence.
- the evolution of programmable hardware architectures for network nodes and data centers.

Table 2.1 Status of 5G deployment and forecast, Reprinted from: [4]

Region	Operator (Number of covered cities)	Launch	Penetration Rate Forecast
Australia	Optus (14), Telstra (46), Vodafone (8) [83]	22/05/2019 [83]	-
Austria	A1 Telekom (129), Drei (Three) Austria (4), Magenta Telekom (T-Mobile Austria) (28) [83]	26/03/2019 [83]	-
Belgium	Proximus (79) [83]	02/04/2020 [83]	-
Canada	Bell (5), Rogers (4), Telus (5) [83]	15/01/2020 [83]	-
Czech Rep.	O2 (2) [83]	19/06/2020 [83]	-
Finland	DNA (21), Elisa (30), Telia (8) [83]	01/07/2019 [83]	-
UE	-	-	29% (2025) [14]
Germany	Telecom Deutschland (20), Vodafone (96) [83]	16/07/2019 [83]	98% (2022) [56]
Gulf Coop. Council	-	-	73% (2026) [1]
Hungary	Maygar Telekom (2), Vodafone (2) [83]	17/10/2019 [83]	-
India	-	-	26% (2026) [1]
Ireland	Eir (19), Vodafone (5) [83]	13/08/2019 [83]	-
Italy	TIM (8), Vodafone (5) [83]	06/06/2019 [83]	-
Japan	KDDI (15), NTT Docomo (35), Softbank (12) [83]	25/03/2020 [83]	-
Korea	KT (85), LGU+ (85), SKT (85) [83]	03/04/2019 [83]	90% (2026) [56]
Latin America	-	-	34% (2026) [1]
Latvia	Tele2 (2) [83]	22/01/2020 [83]	-
N-E Africa	-	-	18% (2026) [1]
Netherlands	Vodafone Ziggo (50% of the Netherlands) [83]	28/04/2020 [83]	-
New Zeland	Vodafone (4) [83]	10/12/2019 [83]	-
Norway	Telenor (4), Telia (2) [83]	13/03/2020 [83]	-
North America	-	-	84% (2026) [1]
N-E Asia	-	-	65% (2026) [1]
Poland	Plus (7), T-Mobile (11) [83]	12/05/2020 [83]	-
S-E Asia and Oceania	-	-	33% (2026) [1]
Spain	Vodafone (22) [83]	15/06/2019 [83]	-
Sub-Saharan Africa	-	-	7% (2026) [1]
Sweden	3-Sweden (5), Tele2 (3), Telia (12) [83]	24/05/2020 [83]	-
Switzerland	Sunrise (384), Swisscom (90% population) [83]	01/04/2019 [83]	-
UK	EE (80), O2 (60), Three (66), Vodafone (44) [83]	30/05/2019 [83]	-
USA	AT&T (335), Sprint (9), T-Mobile (6000), Verizon Wireless (35) [83]	03/04/2019 [83]	-
World	-	-	12% (2024), 50% (2034) [56]

- technology of high frequencies and new radio architectures, advanced radio technologies, antenna technologies,signal processing, and new fully wireless access network architectures.

It is envisioned that 6G will be more a revolution than an evolution in comparison with the previous generations, it will represent a smart compute-connect entity thanks to the exploitation and the convergence of distributed communication, computing and storage, the presence of heterogeneous connected big data resources, integration of sensing, localization and controlling capabilities with Artificial. Thanks to these enabling technologies 6G is intended as a enabler for smart society and ecosystem focusing on several challenging research areas and supporting novel forward-looking scenarios, such as holographic-type communications, ubiquitous intelligence, Tactile Internet, multi-sense experience, and digital twin. It will be based on the pivotal idea of connected and pervasive intelligence derived from the full synergy between AI, its algorithms, protocols and approaches and mobile networks functions in order to implement highly-efficient transmission, optimization, control, and management of resources and networks. In a nutshell, the 6G networks are envisioned to connect everything worldwide for building a virtual digital world, where an intelligent architecture should be required to satisfy the extreme communication requirements. The future 6G network should be sensing-based and data-driven for near-instant, massive and pervasive connectivity with distributed and collective intelligence. Edge intelligence, as a result of AI and edge computing, promises to meet the potential requirements of edge big data with its privacy concerns, but also energy, storage, and bandwidth. While edge intelligence is envisioned to be a solution to fulfill the next generation of intelligent wireless networks, at the same time, mobile edge computing (MEC) provide powerful computation capacity and low-latency services for massive end devices with constrained resources. An additional issue in dealing with the distributed edge intelligence is represented by the increasing in complexity and heterogeneity, especially considering the time-varying channels and network dynamics. Furthermore, the increasing number of smart devices represents a challenge for the management of intelligent network and for the design of 6G networks, which needs liquid self-management and a comprehensive network intelligence. The future wireless network should be able to intelligently analyse the incoming data from the environment and take corresponding actions properly. To give an idea of the numbers, it is forecasted that the number of users in the 6G network will reach nearly 17 billion with 60 ZB data in storage by 2030 [R2], which is far beyond the capacity of 5G networks. [147].

2.1.1 The new challenges of 6G

6G will enable a more pervasive variant of some use cases and applications which have already been introduced in 5G such as IoT, Industry 4.0, virtual reality, and automatic driving but characterized by a better Quality of Experience (QoE) and in a more cost-efficient, energy-efficient, and resource-efficient manner. Meanwhile, it will enable also completely new use cases and disruptive applications that cannot be supported by 5G.
A pivotal point in the design of 6G networks represents also the most challenging aspect and it is the fact that these forthcoming technologies are expected to transform the world into a fully connected network that will turn several concepts into reality. From this perspective, new forward-looking ideas are emerging as the revolutionary concept of the shifting from the "connected things" or Internet of Things (IoT) or Internet of Everything to the "connected intelligence" at the edge of the network [126]. The idea of "connected intelligence", through Artificial Intelligence (AI) and Machine Learning (ML) technologies, imposes much more stringent performance constraints, which inevitably will change fundamental network concepts and will increase the complexity of the network.
The 6G requirements range from very high and reliable data rates (approximately 1 Tb/s in many cases or 100 Gb/s in other situations) to extremely low end-to-end latency, very high energy efficiency and different and very broad frequency bands (up to THz range). Further to this, a peculiar feature is the integration and connection of terrestrial wireless systems with other very heterogeneous ones, such as satellite or networked cars, networked Unmmaned Air Vehicles (UAVs), comporting a rising in complexity. The most crucial key concepts of 6G, representing a real revolution in comparison with the previous technologies, are listed below:

- **Dynamic Topology**: each user with her/his personal device, the plethora of smart devices belonging to the IoT ecosystem but also Autonomous driving Vehicles, UAVs, drones, satellite and radar will embody fast moving network nodes. These nodes connect dynamically to the network which have to provide the best Quality of Service (QoS) and the best performances. This inevitably leads to the need for new mathematics and complex analysis and network design models.

- **THz frequencies**: the need of higher data rates and high spectral and energy efficiency impose the exploitation of the THz band. Hence, "tiny cells", with a radius of only few meters, drive towards much denser deployments. The increasing density of deployment makes it necessary new traffic and mobility management and new congestion control algorithms.

- **Network Functions Virtualization (NFV) and Software Defined Networking (SDN)**: both these technologies are based on virtualization and they are aimed at make it possible network design and infrastructure in software and then to implement it across generic hardware devices and platforms. Specifically, NFV removes network forwarding and generic network functions from the hardware where it runs, leading to the softwarisation of these functions; SDN divides network control functions and network forwarding functions.

- **Artificial Intelligence (AI) and Machine Learning (ML)**: Due to their complexity, it is expected that AI will be crucial for the successful and efficient operation of next 6G networks. Although AI has already been used in wireless communications, such as for channel precoding or traffic control, AI in 6G is expected to facilitate the operation leveraging their complexity. In fact, the vast heterogeneity of applications, users and supporting infrastructure makes it impossible to achieve any guaranteed performance without the introduction of AI. The potential Terahertz or mmWave channels add complexity and non-linearity to the modeling of wireless channels. A pervasive introduction of artificial intelligence at the edge of the network is expected to play a key role in the holistic management of communication, computation, caching and control of resources (see Section 2.1.2).

- **Access Network for Backhaul Traffic**: it is expected that the technologies for networks will require a huge increase of data making the access network for Backhaul not able to cope with it. Free space optical communications and quantum communications could be considered for backhaul to meet the requirements of 6G. It is envisaged the integration of terrestrial, airborne, drones and satellite networks into a single wireless system, by providing connectivity to hotspots and to areas with scarce infrastructure.

- **Moving Networks**: they are a particular category of ad-hoc networks [109, 118, 58] where nodes are in movement and users demand the same level of service as a static infrastructure. Moving networks, due to their highly volatile nature, experience significant quality issues due to the velocity of the vehicles and the attenuation of the radio signals that travel from the base station (BS) to the end devices. Moving devices may also suffer from low signal quality caused by the poor macro antenna coverage of base stations inside vehicles with metallic walls. A solution can be represented by network densification, even if denser deployments lead to higher inter-cell interference. Therefore, advanced algorithms, sophisticated multiantenna solutions, more advanced signal processing techniques and aerial assisted communication can be integrated into mobile nodes to alleviate the above mentioned problems.

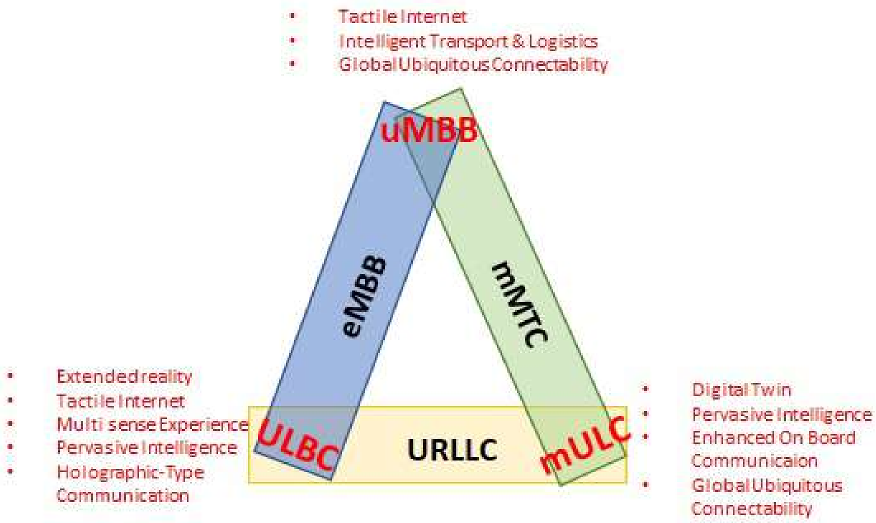

Fig. 2.1 The new usage scenarios of 6G (uMBB, ULBC, mULC)

In order to to satisfy the technical requirements of the 6G applications, in addition to the usage scenarios which have been already defined for 5G (enhanced mobile broad-band (eMBB), ultra-reliable low-latency communications(URLLC), and massive machine-type communications (mMTC)) it is essential the introduction of new ones (see Fig.2.1). 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. URLLC aim at enhance the reliability of 5G-6G networks by supporting transmissions of small amount of data that require very low latency and very high reliability from a specific number of devices. In addition to these, to support high-quality on-board communications and global ubiquitous connectability, it is important to introduce the ubiquitous MBB (uMBB). uMBB are also characterized by bigger network capacity and transmission rate. The uMBB scenario will be the foundation of digital twin, pervasive intelligence, enhanced on-board communications, and global ubiquitous connectability. In addition to the KPIs applied to evaluate eMBB (such as peak data rate and user-experienced data rate), other KPIs become critical in uMBB, i.e., mobility, coverage, and positioning. The so-called ultra-reliable low-latency broadband communication (ULBC) supports the application related to URLLC KPIs but also with high throughput demands (as in the case of immersive gaming, extended reality, Tactile Internet, multi-sense experience, and pervasive intelligence). Finally, mULC combines the characteristics of both mMTC and URLLC, which will facilitate the deployment of massive sensors and actuators in several scenarios [126, 60, 76].

In order to deploy these use cases, 6G systems have to meet extremely stringent requirements

Table 2.2 6G requirements.

KPI	**6G Expectations**
Peak data rate	up to $1Tbps$
User experienced data rate	$1Gbps$
Latency	User plane: 100 μs or even 10 μs
Mobility	maximal speed supported of $1000km/h$
Connection density	10^7 per km^2
Energy Efficiency	$10-100$ times better over that of 5G
Peak spectral efficiency	three times higher spectral efficiency over the 5G ($30bps/Hz$ in the downlink and $15bps/Hz$ in the uplink)
Area traffic capacity	$1Gbps/m^2$
Reliability	success probability of 99.99999%
Signal bandwidth	$1GHz$
Positioning accuracy	cm level
Coverage	the coverage will be globally ubiquitous and will be shifted from only 2D in terrestrial networks to 3D in a terrestrial-satellite-aerial integrated system.

in terms of latency, reliability, mobility, and security, as well as provisioning a substantial boost of coverage, peak data rate, user experienced rate, system capacity, and connectivity density, gaining KPIs from 10 to 100 times better in comparison with 5G. The same "connected intelligence" with AI and ML technologies, imposes much more stringent performances, 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), as well as extremely low end-to-end latency, very high energy efficiency, efficient cloud applications 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 and the requirements of 6G systems [76] (see Table 2.2.
In particular, some representative use cases highlight and define the need of these technical requirements for 6G mobile networks, some of them are listed below [76]:

- **Tactile Internet**: It requires extremely low end-to-end latency, satisfying the $1ms$ of lower reaction time in order to reach the limit of human sense. Together with high reliability, availability, security and throughput it enables a wide range of innovative and disruptive real-time applications. The Tactile Internet will play a urgent role in the field of real-time monitoring and remote management as in Industry 4.0, Smart Grid, remote robotic surgery or patient monitoring.

- **Extended Reality**: Combined with augmented, virtual and mixed ones, Extended Reality is still in its infancy. For an ideal immersion experience, higher resolution, higher frame rate, high dynamic range and more color depth are required, which means a bandwidth demand of over 1.6 Gbps per device. In addition to this, interactive applications, as immersive gaming, remote surgery or remote industrial control require also very low latency and high reliability.

- **Pervasive Intelligence**: The proliferation of mobile smart devices and the emergence of new heterogeneous connected entities such as robots, smart cars, drones lead to an increasing in computation and stringent requirements in storage, power and privacy constraints on mobile devices. To overcome these issues 6G will offer pervasive intelligence in an AI-as-a-Service manner by utilizing distributed computing resources across the cloud, mobile edge, and end-devices. Pervasive, distributed and collective intelligence also facilitates time-intensive AI tasks to avoid the latency of cloud computing when fast decisions or responsiveness are required.

- **Digital Twin**: it is aimed at create a detailed virtual image of a physical object, leading to the so-called cyber-physical convergence. The virtual copy is embedded with several information, properties and characteristics related to the real object with full automation and intelligence. Its full deployment is expected to be realized with the advent of 6G networks.

- **Holographic-Type Communication**: Remote rendering high-definition holograms through a mobile network will bring truly immersive experience. In order to allow people to interact with ultra-realistic objects, Holographic Communication requires high bandwidth on the order of terabits per second with image compression. Furthermore, ultra-low latency for true immersiveness and high-precision synchronization across massive bundles of interrelated streams for reconstructing holograms are required.

- **Multi Sense Experience**: It is based on the idea that current communications focus only on optical and acoustic media even if human beings have five senses. The involvement of smell and taste can create fully immersive experiences, for instance related to the fields of food or texture industries, and the application of tactile communication will play a crucial role in remote surgery, remote controlling, and immersive gaming, all these applications bring a stringent requirement on low latency.

- **Global Ubiquitous Connectability**: The 6G system is envisioned to make use of the synergy of terrestrial networks, satellite constellation, and other aerial platforms to realize ubiquitous connectability for global uMBB users and wide-area IoT applications, also in remote, sparse and rural areas which have no access to the elementary ICT services.

- **Intelligent Transport and Logistics**: For 2030 and beyond it is expected that millions of autonomous vehicles and drones will provide a safe, efficient, and green movement of people and goods. These connected and autonomous vehicles have stringent requirements for what concern latency and reliability but also the need for coordination and context-awareness.

- **Enhanced On-Board Communications**: 6G is expected to be an integrated system among terrestrial networks, satellite constellation, and other aerial platforms to provide fluid 3D coverage, offering high-quality, low-cost, and global-roaming on-broad communication services.

For further up-to-date details on very recent 6G studies, see Table 2.3.

2.1.2 Edge Intelligence

Edge Intelligence (EI), powered by AI is considered as a key missing element in 5G networks and will be a key enabling factor for next 6G systems, in order to support their high performance, new functions, new services [111, 147] and making it possible to satisfy the stringent requirements of use cases such as URLLC (contributing to low latency) or mMTC (providing distributed computing power).
In the last years and in many fields from academia to industry, it is growing the interest for EI due to the proliferation of ubiquitous and heterogeneous devices, from hand-held devices to industrial robots, which make available an increasing amount of data. In fact, the wide multiplier of smart devices, terminals and diffusion of mobile computing and of the Internet of Things (IoT) with its sensors are generating a huge amount of data of the order of ZB. These devices which generate and consume data are commonly located at the edge of the network, in near proximity of end users or monitored systems. Hence, computation need to be shifted from centralized models based on cloud computing towards Edge Computing (EC) which is a distributed form which moves part of the processing and data storage to edge network nodes. In this way, storage and computing are physically and logically close to the data providers and end users improving performance, allowing traffic and new ultra-low latency services. The combination of EI and 6G will significantly contribute to these aspects and to the realization of 6G usage scenarios discussed above.
In this context, it is crucial the definition of Multi-Access Edge Computing or Mobile Edge

Table 2.3 Research works about 6G paradigm

Reference	Year	Keywords
[5]	2020	6G, wireless communications, terahertz band, intelligent communication environments, pervasive artificial intelligence, network automation, all-spectrum reconfigurable transceivers, ambient backscatter communications, cell-free massive MIMO, Internet of NanoThings, Internet of BioNanoThings, quantum communications.
[41]	2020	5G, 6G, artificial intelligence, automation, beyond 5G, data rate, massive connectivity, virtual reality, terahertz.
[60]	2020	6G mobile communication, 5G mobile communication, Reliability, Wireless networks, Internet of Things, Intelligent sensors.
[68]	2021	Edge intelligence, 6G, Ultra-reliable low-latency, COVID-19, Internet of drones, Holographic communication.
[76]	2021	6G mobile communication, Industries, Wireless communication, Wireless sensor networks, 5G mobile communication, Artificial intelligence, Vehicles.
[79]	2021	Massive MIMO, holographic beamforming, Internet of everything (IoE), Machine learning, Distributed security.
[105]	2020	Emergency Service, Healthcare, 5G Communications, 6G Communications, Wireless Communications, Internet of Things, Internet of Everything, Vehicular Technology, Drones, Mobile Hospital, Hospital-to-Home Services, Fire Control, Accidental Services, Natural Disaster.
[111]	2020	Computer Science - Distributed; Parallel and Cluster Computing; Artificial Intelligence; Networking and Internet Architecture.
[119]	2019	6G mobile communication, 5G mobile communication, Market research, Wireless communication, Sensors, Wireless sensor networks.
[126]	2020	Complex systems, complex networks, networked complex system, 6G, wireless communications, wireless networks, mobile communication networks, modeling.
[139]	2020	6G, AI/ML driven air interface, network localization and sensing, cognitive spectrum sharing, sub-terahertz, RAN-Core convergence, subnetworks, security, privacy, network as a platform.
[143]	2020	Edge Computing, Edge Intelligence, Deep Learning, Artificial Intelligence, Deep Neural Networks.
[147]	2022	Artificial intelligence, 6G mobile communication, Wireless networks, Wireless communication, Data models, Training, Task analysis.
[154]	2019	6G wireless networks, intelligent information society, intelligent 6G networks, space exploration, Wireless sensor networks, Videos, Wireless networks.
[157]	2020	6G mobile communication, radio spectrum management, signal detection, synchronisation, telecommunication network reliability.

Computing (MEC) [54] which represent a enabling technology for 5G and beyond networks. This architecture provides that a mobile edge runs a mobile edge platform which facilitates the applications' executions at the edge. MEC applications and services are connected with the cellular domain through the standardized APIs. From what concern the data analytics EI is based on the idea of the development of solutions at or near the place where data are generated and consumed. In this way, edge intelligence allow to reduce latency, cost, to improve security. From the network point of view, EI refers to intelligent devices and functions deployed at the edge of the network. Therefore, it can be envisaged how the evolution of telecommunication infrastructures towards 6G will be strictly related to AI, moving intelligence from the central cloud to edge computing resources. In addition, this kind of distributed intelligence is particularly necessary in those situations where machines and human cooperate and intelligent autonomous systems are envisaged.

In order to be able to process and filter data at the edge end nodes need an increasing level of capacity and with the development of levels of AI at the edge, it is possible give nodes some AI features, as the ability to learn progressively from the context and share what they learn with other edge nodes to provide, collectively, new added value services or optimized services. Perhaps the edge devices are likely to be mobile and thus, powered with capacity-limited batteries and storage, which is used both for computation and communication. To have no impact on the cost of these enhanced end devices it is crucial to rely on cheaper nodes which execute less sophisticated computations and take advantage of the cooperation with other devices. This approach leads to a common and distributed network intelligence for the entire system instead of pointing at a single node, enabling scalability, adaptability and resilience. Thanks to learning algorithms on edge devices, realized using AI techniques such as reinforcement learning [73] and game theory [103], the nodes become able to adapt themselves to changes in the system, altering their behaviors and acting in cooperation with the collective aim at achieving an overall successful result for the system. To this aim it is crucial to allow software to be "liquid" and to "flow" from one device to another. Without liquid software as a part of the future 6G networks, the computation cannot be easily relocated after the design time and we have to decide where to locate the intelligence at the network topology "a priori". A solution in this sense is represented by microservices [92] able to develop modular lightweight application components which can be individually deployed on-demand to build the application workflow. Differently from monolithic software applications, whose modules cannot be executed independently and are unsuitable for distributed systems, microservices are cohesive, autonomic, replaceable and deployable independent processes interacting with each other through standardised interfaces [34].

In addition to these aspects, novel and future 6G applications require real-time feedback to

be effective and address challenges from the real-world scenarios, for instance in the case of self-driving cars, traffic and logistics management systems, telepresence, virtual, augmented or extended reality. These challenges cannot be addressed only considering a reduction of latency and an increasing of network bandwidth but it becomes crucial considering online learning models together with time usually spent to collect training data and to define actions. To reduce these time intervals they are crucial efficient distributed training model, data re-utilization and dynamic decision making based on all the knowledge available from different models and data sources. Furthermore, a main aspect is identifying the characteristics of the network dynamics in the design of these distributed AI algorithms. It is crucial to introduce mechanisms to adopt continuous knowledge acquisition through continual learning methods such as online learning and reinforcement learning.
Finally, another main goals of edge computing, and justification for its need is the maintaining of the required Quality of Experience (QoE) for users, related to network connectivity and application execution improvements, and adaptation to the dynamic environment and user mobility. A key challenge in this direction is understanding the user context (context-awareness) through both a large-scale analysis of user behavioural patterns and real-time activity in the environment. Further challenges are introduced by user mobility which often bring hand-held devices which share dynamic edge resources.

2.2 The need for new and complex approaches

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 in the application of the complex systems approach. In fact, mobile communication networks, especially the forthcoming 6G are a typical example of systems which are in continuous expansion, and characterized by an high level of interdependence among their very heterogeneous components. The design, monitoring, modeling and control of the behaviours of such systems represent a crucial issue to be addressed for which it is essential the introduction of new approaches able to provide models, theories and mechanism suitable for the future 6G networks which are moving from closed hierarchical or semi-hierarchical structures to open and distributed, networked systems. The typical operation of these networks with denser deployments, more base stations, countless users, as well as the new technologies such as the AI, Tera hertz (THz) band communications, softwarisation of networking functionalities and the dynamic orchestration of networked services render any known traditional information theory incapable to directly model their behavior and dynamics.

Complex systems theory represent the most suitable tool for those systems which can be described as [126] decentralized, non-hierarchical, dispersed, and distributed “networks”, involving references to topic like emergence, adaptability, self-organization, evolution, adaptability, resilience, robustness, decentralization, flexibility, and speed. Complexity theory studies how patterns emerge through the interaction of many interacting elements mainly through interrelated approaches: finding statistical properties (such as path length or degree distribution), characterizing the structure and dynamic behavior of networked systems, building models of networks that explain and help understand how they are created and how they evolve and then studying pattern formation and evolution. In other words, to understand how a complex system develop its collective phenomena we must initially understand not only the behavior of its constituent elements but also how they act together and with the external environment.

In the design and monitoring of communication networks the network anatomy characterization is a crucial aspect to be investigated, as the structural and evolutionary properties of networks affect their functions, unveiling the interplay between the structure of a complex network and its dynamics. In particular, in the last few years it becomes clear that most real communication networks, such as the Internet, the World Wide Web (WWW) or the mail network, present similar topological properties as in the complex network structure. The main characteristics that real communication networks have in common with complex networks are large scale topology, decentralized/distributed resource management, heterogeneity of constituents, relatively small average path length, high clustering coefficient, power-law degree distribution.

In addition to these, we can consider a set of attributes to characterize communication networks which motivate the need for a complex network perspective:

- **Structural Complexity**, in order to shed light on the evolutionary mechanism which shape the topology of a network and for the design of new design models based on theoretical foundation such as random networks, small-world networks and scale-free networks [6, 31] which preserve the most important empirical features. The modeling and the characterization of the network’s structure lead to a more deep knowledge about its dynamical and functional behaviour. Furthermore, the structural complexity of a network and its heterogeneity is influenced from both node and connection diversity. A network can consist of various nodes which interact with each other through several kind of links, having different weights and directions. Hence, the wiring diagram of the network affects its functional robustness, resilience and determines the emergence of dynamical collective behaviours like cooperation or spreading.

- **Network Evolution**. The graph of a communication network can be dynamic and change over time. This is a pivotal aspect of dynamically changing environment like the WWW, mobile or ad-hoc networks where links are created and lost time by time. For this reason, the evolution of a communication network correspond to the evolution of a complex adaptive network, leading to multiple paths through which the system evolves.

- **Dynamical Complexity**. 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. It is crucial understanding how an enormous amount of interacting dynamical systems (e.g., mobile user equipment (UEs), mobile nodes, ultra-dense cells, sensor nodes, etc) will behave collectively, given their individual non linear dynamics. Network problems such as congestion control, fault and attack tolerance, error resilience, decentralized/ distributed operation, can be addressed based on concepts arising from the dynamical processes of complex networks.

In order to give a more precise definition of 6G networks they can be considered as complex adaptive systems [126] as complex because they are made up of multiple heterogeneous interconnected elements and adaptive as they have the capacity to learn and change over time based on experience, knowledge and context-awareness, which take into account internal and external processes and interactions. Resorting on tools of complex adaptive networks means being capable of considering new aspect and emerging properties which are crucial in the analysis and design of future communication networks:

- **Many interacting parts**, the dynamically interconnected nodes in which act as elements of the system. These elements interact with each other and with the environment in an unpredictable and unplanned way. From all these interactions equilibria emerge and form patterns.

- **Non linearities**, 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 in a additive way.

- **Evolution and Cooperation**, the elements of the complex system may cooperate or compete in different times. The emerging behaviours are primarily a consequence of its constituent elements having different attributes and capabilities and of their links in accordance to which they can perform multiple and diverse tasks. Evolution results from the process of creating linkages between elements so that the result will be successful in the environment. Hence, the essential ability of an evolutionary network is its ability to create cooperative links leading to an overall common good in the environment. It is crucial also considering how the interactions among individuals related to the interactions of elements within a system which have an effect on environment changes.

- **Emergent Behaviou**r, emergent phenomena occur due to the pattern of interactions (non-linear and decentralized) among the elements of the system over time. It is referred to how the behavior of the system at a larger scale arises from the microscopic structure, behavior and relationships on a finer scale. One of the main points is that emergent behaviour are observable at a macro-level, even if they are generated by micro-level elements.

- **Degeneracy**, which is defined as the ability of structurally different elements to perform the same function yielding the same output. This is a pivotal feature of biological systems, as an inevitable result of natural selection, increasing robustness and adaptability. In other words, degeneracy enables robustness and evolution through diversity, which is essential properties of complex systems.

- **Adaptability**, which is the ability to adapt to external changes thanks to compensatory internal feedback process and changes. In complex systems, the interactions among the constituent elements are allowed to change and the actions of the adaptive unit can affect the whole environment which, in turn, feeds information back to the adaptive system. Therefore, adaptation can be seen as a computation emerging from the multiplicity and recursion of simple elements or subsystems.

- **Self-Organization**, which is the evolution of a system into a organized form, without external control; the organization of the system results from the interactions among its components. The dynamics of a self-organizing system are typically non-linear, because of circular or feedback relations between the components. A complex adaptive system is continually self-organizing through the process of emergence and feedback.

- **Decentralization**, it is essential to provide higher level of robustness and scalability than in centralized architectures, reducing the dependence on a few central nodes. Decentralized systems, where each executive component makes its own decisions and executes only these decisions, provide adaptability and intelligence as the system can be ‘smarter’ than its constituent smartest element.

- **Robustness**, it refers to structural or other properties of a system which allow it to tolerate perturbations or variation (such as the removal of a node in the network) in its internal structure or external environment without malfunctioning or altering its structure or dynamics.

- **Resilience**, it is the capacity of a system to absorb or utilize an event or a change which pervade it, without a qualitative change in the structure of the system. When networked systems break down or are subject to attack, problems may affect the whole structure, disabling part of the network and the resilience is the ability to respond to those events in a way that rectify themselves.

2.3 Complex Networks characterization

The complex networks research area has attracted interest in the last years because until recently the term "complexity" was often misused and confused with "complicated". Actually, although the stem of both these words refers to a system consisting of multiple parts, complicated systems are understandable applying a reductionist approach and, as a consequence, understanding the whole system is equal to understand its individual parts. On the contrary, in complex systems understanding the individual parts is not enough to understand the system as a whole. In order to catch and understand many aspect of our environment it is necessary an approach that starts from the notion of multiple system parts, but focuses on understanding the relationships between those parts, as in the complex case [102]. Traditionally science rejected complexity due to three main principles:

- Reductionism: decomposite the knowledge of a system in its basic elements.
- Disjuction: separate the disciplines.
- Universal Determinism: the causal determinism, if the precise location and time of every atom in the universe is known, their past and future values can be calculated from the laws of classical mechanics.

The concept of complexity appeared in conjunction with the second law of thermodynamics which accounts for the irreversibility of systems and the asymmetry between the future and the past, as opposite to the perfect, ordered, and determinist traditional vision. Starting from the principle that the whole is more than the sum of its parts, complex systems should not be defined only considering their parts individually but also by the relationships between them. As a result, the concept of organization becomes crucial, as the organization of system parts results in emergent and collective dynamics.
A crucial property of these systems is that a big amount of simple units are able to trigger

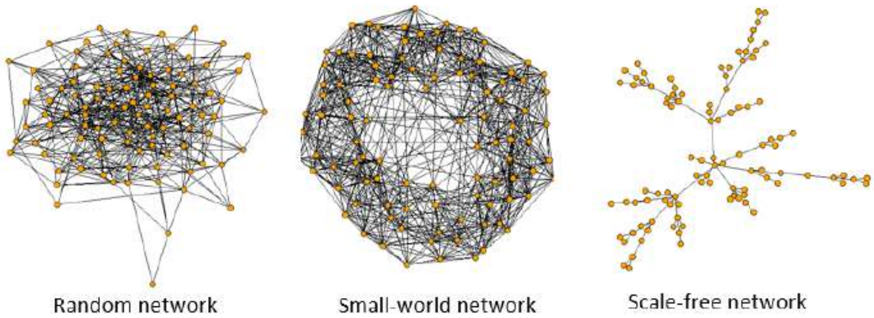

Fig. 2.2 Network modeling paradigms.

unpredictable collective phenomena because the connectedness among these simple units make a more complex entity, which represents more that the simple sum of its part, called network. For this reason, the network science represents the most suitable tool to highlight the structural patterns among elements constituting a wide range of complex systems, making it possible to deepen the analysis of the connectedness of the systems' elements and how they develop its collective behaviour, interacting with each other, and with the environment. The recent progress in the characterization of complex systems, giving rise to support of network modeling, results in the introduction and study of several network paradigms, which are expected to be relevant for 6G [6, 31, 126] (see Fig. 2.2.

2.3.1 Random Graphs

In the past, the trend was to consider complex networks as completely random structure. This model is based on the work of of Alfred Renyi and Paul Erdos [126, 32, 52] who for the first time questioned the process of formation of networks. In accordance with their studies nodes have equal probability of connecting with each other. This network paradigm is still widely applied in many fields, especially as a benchmark or null model for empirical studies.
Random graph networks are characterized by: a low average path length, a small clustering coefficient and a degree distribution following a Poisson distribution. The latter aspect means that even if not all nodes are the same number of connections, most of them have a degree fluttering around a small average value. Random networks are not highly interconnected, therefore they are intolerant to accidental failure; more in detail, the connectedness of random network decays steadily when nodes fail, breaking into smaller and separate graphs incapable of communicate.

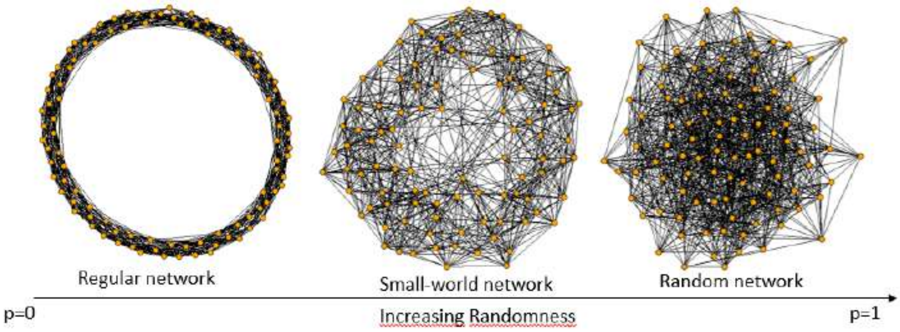

Fig. 2.3 A Small-world network is defined as a topology between a regular lattice network and a random network.

2.3.2 Small-World Networks

Watts and Strongatz in 1998 [142] introduced a new class of network paradigm in order to provide a more suitable framework to study real-world complex networks. Small-world networks are a interpolation between highly clustered regular lattices and random graphs and they are characterized by a high degree of local clustering, a relative short average path length, known in literature as the "six degrees of separation" property. Watts and Strongatz considered a simple model starting from a ring lattice of finite dimension with N nodes connected to their K adjacent neighbours and replacing the original links by random ones with a probability $0 \leq p \leq 1$; where $p = 0$ stay for order and $p = 1$ randomness (as in Fig.2.3). They found also that small-world display enhanced signal propagation speed, computational power and synchronizability which have implications in many real systems like telecommunication networks where small-world connectivity' might improve the ease with which data diffuses through the system. The model have some limitations, for instance it does not give information on how nodes use short links to reach remote nodes or the effect of mobility or the robustness, efficiency or scalability of these networks. Many real world networks such as social networks, neural networks or C.elegans show small-world behaviour but issue derive from how apply it to engineered dynamic systems such as Mobile Ad-hoc networks (MANETs), Wireless Sensor Networks (WSNs) or 6G networks.

2.3.3 Scale-Free Networks

In the late 1990s, researchers tried to explore and explain the functionalities and the structure of the World Wide Web, those research efforts led to discovery that, particularly thanks to the work of Albert and Barabasi [6] for most large networks the degree distribution significantly deviates from a Poisson distribution. More in detail, for many real networks, including the

WWW, the Internet or the mail network the degree distribution follows a power-law tail $p(k) \sim k^{-\gamma}$ defining the probability of a node to have k edges.

These networks topologies were introduced as a universal paradigm of network evolution based on network dynamics. Differently from the small-word model characterized by isolated cluster of high interconnected nodes, scale-free network consist of highly connected hubs holding together the network. In addition, random and small-world networks are formed by a fixed number of nodes N randomly connected or rewired; new edges are placed randomly, hence, the provability that two nodes are connected (or their link is rewired) does not depend on the node's degree. These two aspects do not correspond to most real world networks as WWW or the Internet, therefore, the mode of Barabasi and Albert is based on tho concepts: growth and preferential attachment. The growth is referred to the continuous addition of new vertices and edges to the existing network, for instance the WWW grows exponentially with the addition of new pages. Preferential attachment indicates the tendency for a new node to have higher probability of connecting to the existing nodes with higher connectivity (or degree), the so-called 'rich-gets-richer'. For instance, in the web, a new page is more likely to be added to well known and popular ones. 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 considers the preferential attachment mechanism, such that 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. To sum up, Scale-free networks are characterized by a low avarage path length, a varying clustering coefficient (it decrease as the node degree increase) and by a power law degree distribution.

For what concern the robustness against random failures, thanks to their heterogeneous topology, in fact, when a failure occurs the likelihood that a hub be affected is almost negligible and also in the case if such event occurs, the network will not lose its connectedness, which is guaranteed by the presence of the other hubs. At the same time, the presence of few hubs makes the scale-free networks more vulnerable to targeted attacks. To this extend, if few major hubs are taken out of the network (targeted attack), it simply falls apart and is turned into a set of isolated graphs. Therefore, it becomes crucial evaluating how many hubs are essential for the robustness of a given network.

2.3.4 Proximity Networks

The shifting from a "rigid hierarchical - hardware first - to a more at and flexible- software first implementation", which is envisioned for the 6G precipitates in the need of complex networks analytical models and tools beyond the aforementioned ones. The user mobility and

miniaturization will be crucial in this change of paradigm, making even more relevant aspect such as reconfigurability and adaptiveness. In accordance with recent trends mobility cannot be applied only to the end hosts (often coupled with human behaviours) but to all the network devices, for instance considering moving base stations on UAVs or mobile phones behaving as base stations. In this context a paradigm which is particularly valuable is represented by human proximity networks. These networks are a particular kind of time-varying graphs representing the close-range proximity among human beings in a physical space. The nodes are wired considering linked nodes that have been close to each other for some extent of time. It could be useful empirical data about who is close to whom at what time. Proximity networks are critical in the understanding of the spreading of disease, the efficiency of information dissemination, device to device (D2D) communications and greedy routing processes in ad-hoc networks where proximity creates opportunistic contacts. This aspect shed light on the importance to undertake a Dynamic Network Analysis based on tool like Temporal Graphs which are able to highlight crucial aspect of the current and forth-coming Dynamic Internet [109, 58, 118, 72].
The software-based implementation of the network which promotes adaptivity and reconfigurability together with the mobility of user and intermediary nodes, make the network dynamic in nature. This nature promotes the adoption and the development of innovative and alternative mathematical frameworks for the analysis of complex systems, deviating from the traditional approaches. The fields of multiplex networks, temporal networks, epidemics and EGT, which have appeared and belongs to different research fileds, are highly relevant to the current "dynamic" internet. These tools and their properties will be explained more in detail in the next chapters of this thesis.

Chapter 3

Multilayer Networks

Overview: A complex system is fully described by the connectedness of its constituents and the network representation of the nodes, belonging to them, which interact to each other via multiple links. A standard approach for network description generally consists of analyzing the aggregate graph, that includes all links between nodes but neglects important information, resulting in a losing knowledge in terms of structural complexity and connectivity. In fact, the relationships and interactions between nodes in many real-world systems can be different for relevance, context and meaning [24, 96, 29]. To preserve the knowledge related to the different interactions in multiple layers it is crucial introducing the multiplex dimension of the network. It enables us to better quantify information encoded in terms of collective and emergent behaviours and in terms of spreading and diffusion. Multiplex networks, in which nodes can be adjacent to each other, through intra-layer edges or to its counterpart on another layer through the inter-layer ones [24, 29], represent the most suitable network structure for analyzing the emerging dynamical patterns of spreading phenomena, depending on the nature of social ties [122, 47]. The investigation of a multi-dimensional network representation through the multiplex networks enable us to fully characterize the behaviour of a complex system, unveiling interesting structural properties that helps to understand emerging phenomena. The chapter is organized as follows, the first part highlights the limits of traditional monolayer representation, highlighting the benefits of a multi-layer representation. Following the mathematical formulation of multilayer networks and its particular cases, such as multiplex one that will be treated more specifically by listing its measures and properties. Finally, the framework of temporal multiplex networks is introduced.

3.1 The limits of the traditional Monolayer Network representation

The immense majority of phenomena that surround us and take place within us (which influence our social relationships, transform the environment where we live, affect our biological functioning), is the result of the emergent dynamical organization of systems involving a multitude of elementary units (or entities) interacting with each other via somehow complicated patterns [29]. The same organizational patterns characterize apparently very different systems, ranging from data-packet traffic on the Internet to disease spreading on social networks.
Traditionally, network studies were based on an abstraction where systems are represented as graphs: entities or agents of the system are represented as "nodes" (or "vertices") and the relationships among them are modelled using single, static, unweighted 'edges' (or 'links'). Self-edges or multi-edges are ignored.
Although this approach has been quite successful in the past, it represents an oversimplification in many respects [82]. It has been shown as "network theory" is an important tool for modelling and analysing complex systems throughout the social, biological, physical, information and engineering sciences [29, 82] but one of the major effort of modern physics is then providing proper and suitable representations of these systems, moving beyond simple graphs towards more rich and realistic frameworks, able to provide us a valid tool for understanding the observed phenomena, identifying the rules and mechanisms that are lying behind them, and possibly control and manipulate them conveniently. The reason lies on the fact that, often, in real-word systems edges exhibit heterogeneous features: they can be directed, have different strengths (i.e. 'weights') [96], exist only between nodes that belong to different sets (e.g. bipartite networks) [99] or be active only at certain times [72].
Complex networks theory [31] involves interdisciplinary topics and exploits the available "big data" in order to to extract the ultimate and optimal representation of the underlying complex systems and mechanisms. The principle efforts of complex network theory are the extraction of some generic and universal rules describing the structural properties detected ubiquitously, and modeling the resulting emergent dynamics.
Multilayer and multiplex networks explicitly incorporate multiple channels of connectivity and constitute the natural environment to describe systems interconnected through different categories of connections: each channel (relationship, activity, category) is represented by a layer and the same node or entity may have different kinds of interactions (different set of neighbors in each layer). For instance, in the case of social networks, relationships are of different nature and can be modelled in different layers: friendship, vicinity, kinship,

membership of the same cultural society, partnership or coworker-ship and so on.
To shed light on the limitations of the monolayer approach, in the following three representative examples from the real world are presented. The first case is the description of transportation networks [29, 104] which are, intrinsically, multiplex (or multirelational systems). In particular, considering the air transportation networks (ATN) we can resort to two different representations. On one hand, traditional single-layer where nodes represent airports, while links stand for direct flights between two airports. On the other hand, a more accurate one, where different commercial airlines are mapped into different layers, containing all the connections operated by the same company. If we want to take predictions about the propagation of scheduled flights' delays or the effects of such a dynamics on the movement of passengers, the proper framework to make predictions is considering the ATN as a multilayer networks.
The second example is borrowed by sociology. A social network is a set of people with some pattern of interactions which take place within different groups (levels or layers) and, therefore, they cannot be modeled using the classic complex networks models with single-layer representations. Considering the issue of spreading information or gossip in a social network [110] such as Facebook, we should take into account that friendships in Facebook may result from relationships of very different origins: two users may share a friendship as they are co-workers or because they are fans of the same football team, or because they occasionally met during their holidays, or for any other possible motivations. Considering the situation where a user becomes aware of an information and he/she wants to share it with his/her Facebook's neighborhood of friends. The user will first select a group of friends he/she believes that may be interested to the topic of the information. Therefore, modeling Facebook as a traditional graph and simulating classical diffusion models could conduct to incorrect conclusions and predictions of the real dynamics of the system. On the contrary, the best way to proceed is mapping each group to different layers and operating the spreading process separately on each layer.
For what concern the biology [29], scientists have entirely sequenced the genome of the Caenorhabditis elegans getting a full mapping the neural network with 281 neurons and around 200 of connections. Neurons can be linked by a chemical link or by an ionic channel, with completely different dynamics and, therefore, the only proper way to describe this network is a multiplex graph with 281 nodes and two layers. In this way, each neuron can play different roles in the two layers, distinguishing those cases in which a node is high central in a layer and marginal in the other.
These examples explain why the last years of research in network science have been characterized by more and more attempts to generalize the traditional network theory by developing

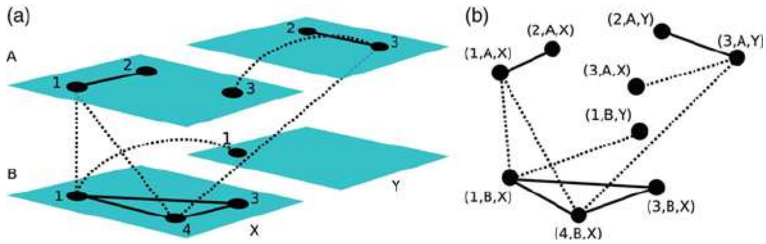

Fig. 3.1 Multilayer Networks. Reprinted figure from [82]

(and validating) a novel framework for the study of multilayer networks. To sum up, the multiplexity represents an extra dimension of analysis which makes it possible unveiling non-trivial dynamics and non-trivial phenomena, through multiple channels of connectivity. and providing the more natural description for systems in which nodes have a different set of neighbours in each layer.

3.2 General Formalism of Multilayer Networks

Complex systems theory studies systems with many interdependent components which can interact through many different channels. The development of this science provides innovative tools to understand many different mechanisms and processes from physical, social, engineering, information and biological sciences. Most complex networks are composed by multiple sub-networks and layers of connectivity, and they are often open, directed, multilevel, multicomponent, reconfigurable networks of networks, placed within dynamically changing environments. They evolve, adapt and transform themselves in accordance with internal and external dynamic interactions which affect the subsystems and the components at both local and global scale.

Observing, understanding, reconstructing and predicting the multiscale and multicomponent dynamics of these systems represent the very challenge, together with the generalization of the "traditional" network theory and the developing of a solid formulation. A lot of work has been done during the last years to understand the structure and dynamics of these kind of systems [82] taking into account notions, such as networks of networks, multidimensional networks, multilevel networks, multiplex networks, interacting networks, interdependent networks, and many others.

In this section the general framework for multilayer networks and its properties and measures will be discussed.

A multilayer network is a pair $M = (G, C)$ where $G = G_\alpha; \alpha \in 1, ..., M$ is a family of (directed or undirected, weighted or unweighted) graphs $G_\alpha = (X_\alpha, E_\alpha)$ which represent the layers of

M and $C = \{E_{\alpha,\beta} \subseteq X_\alpha * X_\beta; \alpha, \beta \in 1, ...M; \alpha \neq \beta\}$ is the set of interconnections between nodes of different layers G_α and G_β with $\alpha \neq \beta$.
The elements of C are called crossed layers, and the elements of each E_α are called intralayer connections of M in contrast with the elements of each $E_{\alpha\beta}(\alpha \neq \beta)$ which are called interlayer connections.
The set of nodes of the layer G_α will be denoted by $X_\alpha = \{x_1^\alpha, ..., x_{N_\alpha}^\alpha\}$ and the adjacency matrix of each layer G_α will be denoted by:

$$A^{[\alpha]} = (a_{ij}^\alpha) \in \mathbb{R}^{N_\alpha * N_\alpha} \tag{3.1}$$

where: $a_{ij}^\alpha = 1$ if $(x_i^\alpha, x_j^\alpha) \in E_\alpha$, $a_{ij} = 0$ otherwise; for $1 \leq i, j \leq N_\alpha$ and $1 \leq \alpha \leq M$.
The interlayer adjacency matrix corresponding to $E_{\alpha,\beta}$ is the matrix:

$$A^{[\alpha,\beta]} = (a^\alpha \beta_{ij}) \in \mathbb{R}^{N_\alpha * N_\beta} \tag{3.2}$$

given by: $a_{ij}^{\alpha\beta} = 1$ if $(x_i^\alpha, x_j^\beta) \in E_{\alpha\beta}$, $a_{ij} = 0$ otherwise.
The projection network of M is the graph $proj(M) = (X_M, E_M)$ where: $X_m = \bigcup_{\alpha=1}^M X_\alpha$, $X_m = (\bigcup_{\alpha=1}^M E_\alpha) U (\bigcup_{\alpha,\beta=1,\alpha\neq\beta}^M E_{\alpha\beta})$. The adjacency matrix of $proj(M) = (X_M, E_M)$ is denoted by $\overline{A_M}$ [30].
In addition, a multilayer network can have any number d of aspects, and we can define a sequence $L = \{L_a\}_{a=1}^d$ of sets of elementary layers such that there is one set of elementary layers L_a for each aspect a (see Fig.3.1). Using the sequence of sets of elementary layers, it is possible to construct a set of layers of the multilayer network by assembling a set of all of the combinations of elementary layers using a Cartesian product $L_1 * ... * L_d$ and nodes can be absent in some of the layers [82].
In general, by exploiting this multilayer representation, we simultaneously consider:

- the links within the different groups,
- the nature of the links and the relationships between elements that may also belong to different layers,
- the specific nodes belonging to each layer involved.

The framework of multilayer network extends different mathematical objects displaying a multilayer network structure, such as multiplex networks, networks of networks, multidimensional networks, etc. which can be represented exploiting the mathematical formulation of multilayer networks, by only introducing some constraints.The mathematical properties of these mathematical objects can be summerized as follows:

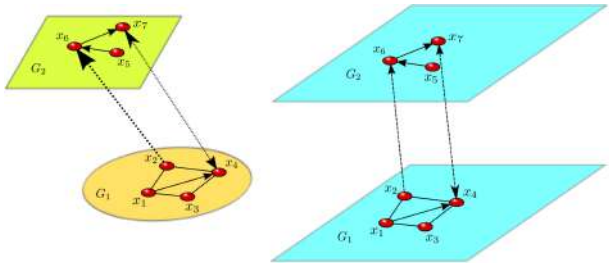

Fig. 3.2 Interacting networks. Reprinted figure from [82]

- **Interdependent network**, a collection of different networks, corresponding to the various layers, whose nodes are interdependent to each other. This means that there is a interdependence of the nodes of one layer with another node, which is a control node, belonging to a different layer [35]. These dependencies constitute constraints, and are represented by additional edges connecting the different layers. This structure is known as mesostructure. We can consider an interdependent (or layered) network as a multilayer network by identifying each network with a layer.

- **Interconnected networks**, if we consider a set of interacting networks $G_1, \ldots, G_L$, they can be modelled as a multilayer network of L layers and whose crossed layers $E_{\alpha,\beta}$ correspond to the interactions between networks G_α and G_β [29].

- **Multidimensional networks**, considering an edge-labeled multigraph (or multidimensional network) as a triple $G = (V, E, D)$, where V is the set of nodes, D is the set of labels, representing the different dimensions, and E is the set of labeled edges, defined by the triples $E = (u, v, d); u, v \in V; d \in D$. The rule is that, considered a pair of nodes $u, v \in V$ and a label $d \in D$, there could be only one edge (u, v, d). In the particular case of a directed graph, the edges $(u, v, d) \neq (v, u, d)$. Fixed the cardinality of D equals to m, each pair of nodes in G can be connected by at most m possible edges. If we also consider the weights, the edges become quadruplets (u, v, d, w), where $w \in R$ is the weight of the relation between nodes $u, v \in V$ and labeled with $d \in D$. Furthermore, a multidimensional network $G = (V, E, D)$ can be modelled as a multiplex network and, hence, as a multilayer network by mapping each label to a layer [29].

- **Multilevel networks**, - taking into account a graph $G = (X, E)$, a multilevel network is a triple (X, E, S), where $S = (S_1, \ldots, S_p)$ is a family of subgraphs (or slices) $S_j \in S$, with $S_j = (X_j, E_j), j = 1, \ldots, p$ of the network G, which is the projection network of M, such that:
$$X = \bigcup_{j=1}^{p} X_j; E = \bigcup_{j=1}^{p} E_j \tag{3.3}$$

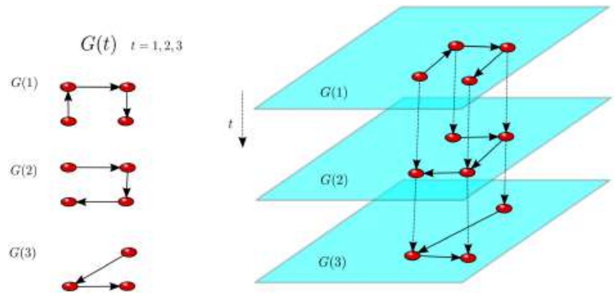

Fig. 3.3 Temporal Network into multilayer. Reprinted figure from [82]

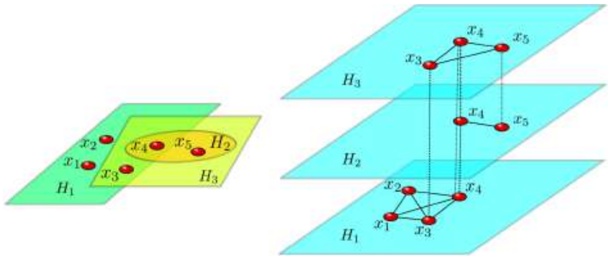

Fig. 3.4 Hypergraph. Reprinted figure from Ref [82]

Clearly, a multilevel network $M = (X,E,S)$ can be seen as a multilayer network, with layers $S_1,...,S_p$ and crossed layers $E_{\alpha,\beta} = (x;x); x \in X_\alpha \cap X_\beta$, and also as a multiplex network if $X_\alpha = X_\beta$ for all $1 \leq \alpha, \beta \leq p$.

- **Temporal networks**, A temporal network $(G(t))_{t=1}^{T}$ can be represented as a multilayer network with a set of layers $G_1,...,G_T$, where $G_t = G(t)$, $E_{\alpha,\beta} = \emptyset$ if $\beta \neq \alpha + 1$ (where t is an integer, and not a continuous parameter) [72, 129], while crossed layers are given by:
$$E_{\alpha,\alpha+1} = (x,x); x \in X_\alpha \cap X_{\alpha+1} \tag{3.4}$$

- **Hypergraphs**, A hypergraph is a pair $H = (X,H)$, where X is the set of nodes and $H = H_1,...,H_p$ includes (non-empty) subsets of X, known as hyperlinks of H. Therefore, considering a graph $G = (X,E)$, an hyperstructure S is defined as a triple (X,E,H) constituted of the vertex set X, the edge set E, and the hyper-edge set H. A hypergraph can be represented as a multilayer network, defining a layer with G_h, a complete graph of nodes $(x_1,...,x_k)$ for each hyperlink $h = (x_1,...,x_k) \in H$, and the interlayer connections are $E_{\alpha,\beta} = (x,x); x \in X_\alpha \cap X_\beta$.

- **Multiplex networks**, a multiplex network [24] $\mathscr{M}$ is a network consisting of L layers $\alpha = \{1,...,L\}$ and N nodes $i = \{1,...,N\}$. It is defined as a set of L networks (or layers)

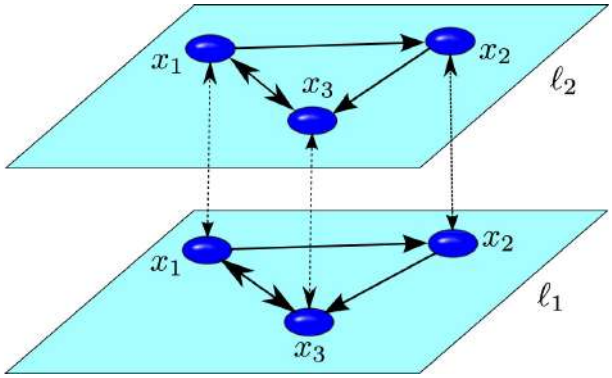

Fig. 3.5 Multiplex Network. Reprinted figure from [82]

$G_\alpha = (V, E_\alpha)$ characterized by a set of nodes referred to vertices V, that is the same for each layer, whereas the set of links E changes in accordance with the layer. Each network G_α is described by the adjacency matrix, denoted by A^α with elements a_{ij}^α, where $a_{ij}^\alpha > 0$, if there is a link between i and j, $a_{ij}^\alpha = 0$ otherwise.

– **Weighted Multiplex Network**, The complexity in connections, can be explored more deeply, taking into account weighted multiplex networks [96], considering that the interactions between nodes may have different intensity reflected by distinct weights. Starting from these premises, the links between nodes could be distinguished not only by the kind of interaction, but also by the weights, reflecting their intensity, capacity, duration or relevance. A weighted multiplex networks is defined as a multiplex network $\mathscr{M}$ consisting of L layers $\alpha = \{1,...,L\}$ and N nodes $i = \{1,...,N\}$. Each network G_α is described by the adjacency matrix, denoted by A^α with elements a_{ij}^α, where $a_{ij}^\alpha = w_{ij}^\alpha > 0$, if there is a weighted link between i and j with a weight w_{ij}, otherwise $a_{ij}^\alpha = 0$.

3.3 Measures for multiplex networks

The vast availability of big data, the rediscovery of old data sets and the improvement of computing capability, has highlighted the necessity to develop a new framework to represent networks whose units interact through more than just one kind of relations. These systems are well modelled through multiplex networks, which are characterised by the fact that all the connections of a given type are embedded into a distinct layer.

In the next paragraphs the most basic measures to characterise the structure of multiplex network are provided, focusing on the properties of nodes, edges, and layers [24]. The relevance of these mathematical tools is such that the scientific interest around their applications is growing, involving several areas: biological, social and technological systems, social networks and telecommunication ones, epidemics and social contagions, transportation networks and brain computing dynamics [120, 104, 7].

3.3.1 Node's Properties

Differently from the traditional mono-layer approach, where node properties are described by scalar variables, node features in multiplex networks are naturally described in vectorial terms.
For instance, for each node i its total number of connections, or **degree**, at layer α is expressed as follows:

$$k_i^\alpha = \sum_{j \neq i}^{N} a_{ij}^\alpha \tag{3.5}$$

and the multilayer degree: $k_i = \{k_i^{[1]}, ..., k_i^{[L]}\}$. A node i is active on a layer α it it is connected to at least another node at that layer, $k_i[\alpha] > 0$. The activity-pattern of nodes can be stored into the node activity vector $b_i = \{b_i^{[1]}, ..., b_i^{[L]}\}$, where $b_i^{[\alpha]} = 1$ if a node i is active on a layer α, $b_i^{[\alpha]} = 0$ otherwise. The total activity $B_i = \sum_{\alpha=1}^{L} b_{ij}^\alpha$ representing the number of layers where a node is active $0 \leq B_i \leq L$. It has been empirically demonstrated that many multiplex networks from real-world are characterised by heterogeneous distributions of node activity which could be responsible for the increased fragility of multiplex networks to random failures [24]. The total number of connections of node i is usually called total or **overlapping degree**:

$$o_i = \sum_{\alpha}^{L} k_i^\alpha \tag{3.6}$$

while the heterogeneity of the number of neighbours of node i across the layers can be measured through the **multiplex participation coefficient**:

$$P_i = \frac{L}{L-1}[1 - \sum_{\alpha=1}^{L} (\frac{k_i^\alpha}{o_i})^2] \tag{3.7}$$

where $P_i = 1$ when the links incident on node i are equally distributed across the layers, and $P_i = 0$ when the node is active only on one layer.
Similar information about the heterogeneity of the distribution of a node's connections across the layers is provided by the **Shannon entropy** of the normalised degree vector:

$$H_i = -\sum_{\alpha=1}^{L} (\frac{k_i^\alpha}{o_i}) \ln (\frac{k_i^\alpha}{o_i}) \tag{3.8}$$

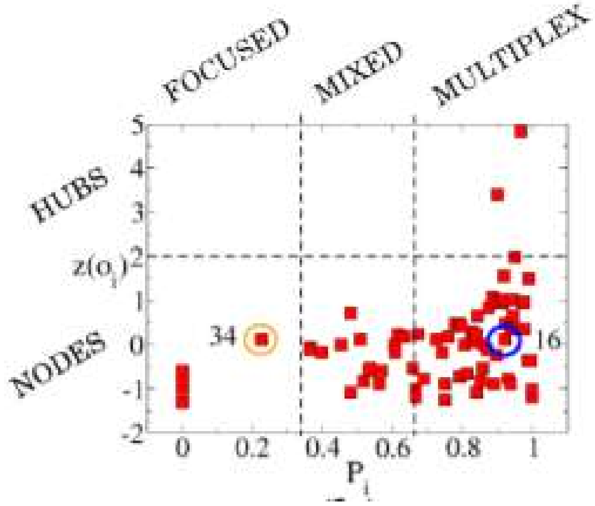

Fig. 3.6 Cartography of the roles of the nodes in a multilayer network in function of the multiplex participation coefficient P_i and the Z-score $z(o_i)$. Reprinted from [22].

The couple of measures (P_i, o_i) can be used to classify nodes via the so-called multiplex cartography, distinguishing nodes' roles such as multiplex hubs (high o_i and high P_i), focused hubs (high o_i and low P_i), multiplex leaves (low o_i and high P_i) and focused leaves (low o_i and low P_i). With respect to the multiplex participation coefficient P_i, it is possible to identify three classes of nodes: focused those nodes for which $0 \leq P_i \leq 1/3$, mixed the nodes having $1/3 \leq Pi \leq 2/3$ and multiplex nodes with $P_i > 2/3$. In the cartography, instead of the overlapping degree itself, it is considered the associated Z-score, which allows to compare multiplex networks of different size:

$$z(o_i) = \frac{(o_i) - \langle o \rangle}{\sigma_o} \tag{3.9}$$

where $\langle o \rangle$ is equal to the average overlapping degree of the nodes in the system; σ_o is the corresponding standard deviation. With respect to the Z-score of their overlapping degree, it is possible to distinguish hubs, for which $z(o_i) \geq 2$, regular nodes for which $z(o_i) < 2$. Taking into account the multiplex participation coefficient P_i of a node and its total overlapping degree o_i we can define six classes of nodes, as depicted in Fig.3.6, where each node is represented as a point of the $(P_i, z(o_i))$ plane [22].
A node can have different roles on the different layers, which allow to define a more detailed definition of multiplex centrality measures where the role of a node explicitly is determined by the whole multiplex structure with all its layers. The **eigenvector centrality** of nodes on

each layer α is the normalised eigenvector relative to the largest eigenvalue of:

$$\tilde{A}^{[\alpha]} = \sum_{\beta=1}^{M} i^{[\alpha,\beta]} A^{[\beta]} \tag{3.10}$$

where $I = i^{[\alpha,\beta]}$ is the influence matrix determining how the centrality of layer α depends on the structure of layer β. In alternative, the contribution of the different layers to the centrality of the nodes can be quantified considering the varying coefficients $i^{[\alpha]}$ with $\alpha = 1,...,M$ of the matrix which is a convex combination of the adjacency matrices of the layers:

$$A^{'} = \sum_{\alpha=1}^{M} i^{[\alpha]} A^{[\alpha]} \tag{3.11}$$

In addition, many real-world networks have a small-world property, the usual distance between any pair of nodes scales logarithmically with the total amount of nodes. Starting from the assumption that not all the nodes are equally relevant in mediating paths between other nodes (which is the main idea between the concept of node betweenness) and that the reachability of a node might significantly depend on the interplay between different layers, the added value, introduced my multiplexity, can be quantified thanks to the **interdependence**.

$$\lambda_i = \frac{1}{N-1} \sum_{j \neq i} \frac{\psi_{i,j}}{\sigma_{i,j}} \tag{3.12}$$

where $\psi_{i,j}$ is the number of shortest paths between i and j using edges in more than one layers, while $\sigma_{i,j}$ is the total number of shortest paths between i and j. λ_i assumes values in the range $[0,1]$ with 1 means a higher advantage for the reachability of node i provided by the interplay of the different layers. The interdependence of multilayer system is obtained by averaging over all nodes: $\lambda = frac1N \sum_i \lambda_i$. In order to define a layer interdependence $\lambda^{[\alpha]}$ we have to take into account the total number of shortest path with at least one link on layer α.

A noteworthy property of real-world networks is the tendency of nodes to form triangles, a phenomenon usually known as transitivity. In single-layer networks, the amount of triangles is typically measured by the average clustering coefficient $C = \frac{1}{N} \sum_{i=1}^{N} C_i$ and C_i is the amount of triads centered on node i. In the case of multiplex networks triads and triangles can extend through the different layers, l-triad (or l-triangle) is a triad (or triangle) using edges from l different layers. It is possible to define two **multiplex clustering coefficients** to quantify the added value provided to transitivity by the multiplex structure.

For a node i the first coefficient $C_{i,1}$ is defined as the ratio between the number of 2-triangles with a vertex in i and the number of 1-triads centred in i, as follows:

$$C_{i,1} = \frac{\sum_{\alpha}\sum_{\alpha\neq\alpha'}\sum_{j\neq i, m\neq i}(a_{i,k}^{[\alpha]}, a_{j,m}^{[\alpha']}, a_{m,i}^{[\alpha]})}{(M-1)\sum_{\alpha} k_i^{[\alpha]}(k_i^{\alpha}-1)} \tag{3.13}$$

The second multiplex clustering coefficient $C_{i,2}$ is defined as the ratio between the number of 3-triangles with node i as a vertex, and the number of 2-triads centred in i. In formulas:

$$C_{i,2} = \frac{\sum_{\alpha}\sum_{\alpha\neq\alpha'}\sum_{\alpha''\neq\alpha,\alpha'}\sum_{j\neq i, m\neq i}(a_{i,k}^{[\alpha]}, a_{j,m}^{[\alpha']}, a_{m,i}^{[\alpha]})}{(M-2)\sum_{\alpha}\sum_{\alpha\neq\alpha'}\sum_{j\neq i, m\neq i}(a_{i,k}^{[\alpha]}, a_{m,i}^{[\alpha']})} \tag{3.14}$$

These measures are defined respectively for $M \geq 2$ and $M \geq 3$, and they are the generalisation of the clustering coefficient to the case of multiplex networks.
In complex weighted networks, weights can be distributed across links in a more heterogeneous or more uniform way. In order to evaluate this heterogeneity we can measure the **strength** $S_i^{[\alpha]}$ and the **Inverse Participation Coefficient** $Y_i^{[\alpha]}$ of node i in layer α, which are defined as follows [96]:

$$s_i^{\alpha} = \sum_{j\neq i}^{N} w_{ij}^{\alpha} \tag{3.15}$$

$$Y_i^{\alpha} = \sum_{j=1}^{N} a_{ij}^{\alpha}/s_i^{\alpha} \tag{3.16}$$

For each layer α, the strength $S_i^{[\alpha]}$ measures the sum of the weights of the links incident upon node i in the considered layer, while the inverse participation coefficient $Y_i^{[\alpha]}$ evaluates unequally the weights of the links of node i are distributed in the considered layer α. $(Y_i^{[\alpha]})^{-1} \in (1, k_i^{[\alpha]})$ characterizes the effective number of links of node i in layer α. If the links of i are uniformly distributed then $(Y_i^{[\alpha]})^{-1} = k_i^{[\alpha]}$, instead if the weight of one link is much larger than the other weights $(Y_i^{[\alpha]})^{-1} = 1$

3.3.2 Layer Properties

it is possible to define the activity-vector for each layer α:

$$d^{[\alpha]} = \{b_1^{[\alpha]}, ..., b_N^{[\alpha]}\} \tag{3.17}$$

where $b_i^{[\alpha]} = 1$ if $k_i^{[\alpha]} > 0$, and $b_i^{[\alpha]} = 0$ otherwise. For each layer α the total **layer activity** $N^{[\alpha]} = \sum_{i=1}^{N} b_i^{[\alpha]}$ describes the total number of nodes with at least one connection in a layer

α, with $0 \leq N^{[\alpha]} \leq N$. The similarity between the activity-vectors of two layers α and β can be measured through the **pairwise multiplexity**, equal to the fraction of nodes of the multiplex which are active on both layers:

$$Q^{[\alpha],[\beta]} = \frac{1}{N}\sum_{i=1}^{N} b_i^{[\alpha]} b_i^{[\beta]} \tag{3.18}$$

Generally, $0 \leq Q^{[\alpha],[\beta]} \leq 1$ with $Q^{[\alpha],[\beta]} = 1$ when all nodes are active in both layers, and $Q^{[\alpha],[\beta]} = 0$ when no node is active on both layers.
The similarity among the patterns of activity in two layers can also be measured through the **Hamming distance**, defined as:

$$H^{[\alpha,\beta]} = \frac{\sum_i b_i^{[\alpha]}(1-b_i^{[\beta]}) + b_i^{[\beta]}(1-b_i^{[\alpha]})}{min(N^{[\alpha]}+N^{[\beta]},N)} \tag{3.19}$$

$H^{[\alpha,\beta]} = 0$ if $d^{[\alpha]} = d^{[\alpha]}$ and while $H^{[\alpha,\beta]} = 1$ when active nodes are active in only one layer. Commonly, multiplex networks are characterised by heterogeneous distribution of pairwise multiplexity and layer activity.
In addition, real-world multiplex networks present correlations among degrees of the same node in the different layers of the network and this property is valid for all the node's properties. More in general, given two layers α and β of a multiplex network and a generic node property ξ_i, the correlation among $\xi_i^{[\alpha]}$ and $\xi_i^{[\beta]}$ is expressed by the **rank correlation coefficient**:

$$\rho^{[\alpha],[\beta]} = \frac{\sum_i (R_i^{[\alpha]} R^{\bar{[\alpha]}})(R_i^{[\beta]} R^{\bar{[\beta]}})}{\sqrt{\sum_i (R_i^{[\alpha]} R^{\bar{[\alpha]}})^2 \sum_j (R_i^{[\beta]} R^{\bar{[\beta]}})^2}} \tag{3.20}$$

where $R_i^{[\alpha]}$ is the rank of a node i at a layer α related to the property ξ and $R^{\bar{[\alpha]}} = \frac{1}{N}\sum_i R_i^{[\alpha]}$ is the average rank. When the property considered is the degree, instead of the generic property ξ, we can define the average degree at layer β of a node that has a degree $k^{[\alpha]}$ at layer α:

$$k^{\bar{[\beta]}} k^{[\alpha]} = \sum_{k^{[\beta]}} k^{[\beta]} P(k^{[\beta]} | k^{[\alpha]}) \tag{3.21}$$

An increasing (or decreasing) trend of $k^{\bar{[\beta]}} k^{[\alpha]}$ signal the presence of positive (or negative) inter-layer degree correlations between layer α and layer β.
The inter-layer degree correlation can be quantified also by using the **pairwise mutual**

information between the degree sequences of the two layers:

$$I^{[\alpha],[\beta]} = \sum_{k^{[\alpha]}} \sum_{k^{[\beta]}} P(k^{[\alpha]}, k^{[\beta]}) \log \frac{P(k^{[\alpha]}, k^{[\beta]})}{P(k^{[\alpha]}), (k^{[\beta]})} \tag{3.22}$$

which is maximal when the degree sequences $\{k_i^{[\alpha]}\}$ and $\{k_i^{[\beta]}\}$ are perfectly correlated (or perfectly anti-correlated), and minimal when they are uncorrelated. A crucial research issue in the field of complex networks, and in particular multiplex networks, is to assess if the presence of more than one interaction layer provides more information about the structure of a system in comparison with a classical mono-layer representation. It is, particularly, interesting quantifying how much information is lost aggregating some or all the layers of a multiplex network to obtain a lower-dimensional representation. Many real-world multiplex networks are not random combinations of the different layers, but their structures are determined by hidden geometric correlations [22].

3.3.3 Edge Properties

Thanks to the existence of multiple layers, a pair of nodes (i, j) can be linked through several edges. Given two layers α and β, the **edge overlap** of the pair i, j is defined as:

$$o_{i,j}^{[\alpha,\beta]} = \frac{o_{i,j}^{[\alpha]} + o_{i,j}^{[\beta]}}{2} \tag{3.23}$$

where $o_{i,j}^{[\alpha,\beta]} = 1$ if i and j are connected at both α and β layers, $o_{i,j}^{[\alpha,\beta]} = 1/2$ if they are connected at one layer only, and $o_{i,j}^{[\alpha,\beta]} = 0$ if the two nodes are not connected. For a generic number of layers L, the edge overlap is defined as:

$$o_{i,j} = \frac{1}{M} \sum_{\alpha} a_{i,j}^{[\alpha]} \tag{3.24}$$

and this measure can be extended to the whole network:

$$o = \frac{2}{N(N-1)} \sum_{i,j \neq i} o_{i,j} \tag{3.25}$$

where the average is computed over all possible pairs of nodes. Considering the average restricted to the pairs of nodes which share at least one edge, the definition is the following:

$$\omega = \frac{\sum_i \sum_{j>i} a_{i,j}^{[\alpha]}}{M \sum_i \sum_j 1 - \delta_{0, \sum_\alpha a_{i,j}^{[\alpha]}}} \tag{3.26}$$

The **multiplexity** is a similar measure of edge correlations which takes values in the range $[0,1]$ and it is defined as:

$$m^{[\alpha,\beta]} = \frac{2 \sum_{i,j} min(a_{i,j}^{[\alpha]}, a_{i,j}^{[\beta]})}{K^{[\alpha]} + K^{[\beta]}} \tag{3.27}$$

where $K^{[\alpha]}$ and $K^{[\beta]}$ are the total amount of edges at layer α and β respectively. A dual quantity is the so-called **edge intersection index**:

$$INT = M \frac{\sum_{i,j=1}^{N} min_\alpha \{a_{i,j}^{[\alpha]}, a_{i,j}^{[\beta]}, \ldots, a_{i,j}^{[L]}\}}{\sum_{\alpha=1}^{M} \sum_{i,j=1}^{M} a_{i,j}^{[\alpha]}} \tag{3.28}$$

which measures the probability of finding a pair of nodes that is connected by an edge on all the L layers of the multiplex network. In conclusion, an additional characterisation of edge correlations can be based on the conditional probability to find a link at layer α given the presence of an edge between the same nodes at layer β.

$$P(a_{i,j}^{[\alpha]}, a_{i,j}^{[\beta]}) = \frac{\sum_{i,j} a_{i,j}^{[\alpha]}, a_{i,j}^{[\beta]}}{\sum_{i,j} a_{i,j}^{[\beta]}} \tag{3.29}$$

If the layer β is weighted, it is possible to consider the conditional probability to have an edge at layer α given its weights on layer β. If this probability increase in function of the weight, this is called edge reinforcement and it is the principle that a stronger link on one layer implies a higher chance to find the same edge on another layer.

3.3.4 Mesoscale Properties

Complex networks are usually characterised by non-trivial structural patterns both at single-node level and, more importantly, at the level of sub-graphs. Statistically significant sub-graphs in single-layer networks are known as motifs and it has been found that a few specific sub-graphs are over-represented in real systems compared to their abundance in equivalent networks obtained by randomising the original graph. A first example of motif in multiplex networks is represented by **multilink** that is the organisation of the edges between the same

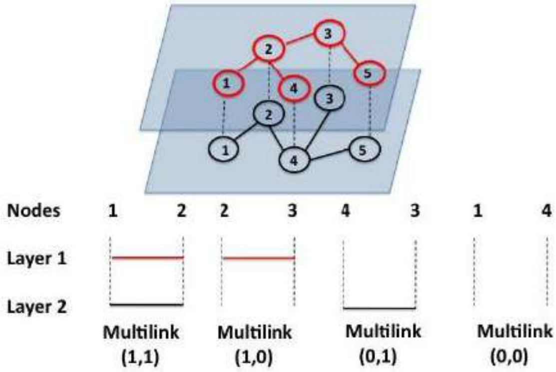

Fig. 3.7 Example of all possible multilinks in a multiplex network. Figure reprinted from [96].

pair of nodes (i, j) across the L layers. In traditional mono-layer networks two nodes can be connected or not by a link, while in multiplex network any two nodes can be connected in multiple ways. Two nodes are connected via a multilink, where the multilink describes the pattern of connections between two nodes [99]. Considering the $\mathscr{M}$ multiplex network, the vector $\overrightarrow{m} = (m_1, m_2, ..., m_\alpha, ..., m_L)$, defined as a multilink, where each element m_α can assume only two possible values $m_\alpha = 0, 1$. The **multiadjacency matrices** $A^{\overrightarrow{m}}$ with elements $A_{ij}{}^{\overrightarrow{m}}$, and the multidegree $k_i^{\overrightarrow{m}}$, defined as [99]:

$$A_{ij}{}^{\overrightarrow{m}} = \prod_{\alpha=1}^{L} [\theta(a_{ij}^{\alpha})m_\alpha + (1-\theta(a_{ij}^{\alpha}))(1-m_\alpha)] \tag{3.30}$$

where $\theta(x) = 1$, if $x > 0$, otherwise $\theta(x) = 0$. These elements allows us to evaluate if exists a multilink between nodes i and j. In order to estimate the structural role of a node in the multiplex network, we evaluate how many multilinks $\overrightarrow{m}$ are incident upon node i through its **multidegree** measure:

$$k_i^{\overrightarrow{m}} = \sum_{j=1}^{N} A_{ij}^{\overrightarrow{m}} \tag{3.31}$$

Also the l-triads and l-triangles used for the definition of node clustering coefficients are multiplex motifs. It is possible to classify motif in three levels: the first level is constituted by connected subgraphs distinguished in accordance with the number of nodes; at the second level the different patterns are identified and classified on the aggregated structure; at the third level the exact multiplex connectivity pattern is identified.

Another crucial feature of networked systems, and multiplex networks, is the trend to clustering of units in tightly-knit groups, forming non-trivial communities. In order to characterise the communities structure of a multiplex network we can consider the normalised mutual information which, given two layers α and β and their partitions in communities P_α and P_β, is equal to:

$$NMI(P_\alpha, P_\beta) = \frac{-2\sum_{m=1}^{M_\alpha}\sum_{m'=1}^{M_\beta} N_{mm'} \log\left(\frac{N_{mm'}N}{N_m, N'_m}\right)}{\sum_{m=1}^{M_\alpha} N_m \log\left(\frac{N_m}{N}\right) + \sum_{m'=1}^{M_\beta} N_{m'} \log\left(\frac{N_{m'}}{N}\right)} \tag{3.32}$$

with $N_{mm'}$ is the number of nodes in common between community m of partition P_α and community m of partition P_β, N_m and $N_{m'}$ respectively the number of nodes in the two communities m and m'. The richness of multiplex networks in comparison with single-layer structure is reflected in its communities which cannot be obtained by considering its layers individually. Some communities might exist only in one layer, other communities can overlap on many layers and there are also communities existing only when the whole structure of the multiplex network is considered. In [99] authors propose a multilink community detection method for multiplex networks which extends link communities to the multiplex network framework and it is based on the similarity of incident multilinks. The similarity between two multilinks is measured by comparing the local structure of the multiplex against a local, maximum entropy null model, describing the knowledge of the multiplex in a way that is maximally evasive to the multi-layer structure. To construct a hierarchical clustering of multiplex networks the similarity the similarity between incident multilinks is evaluated by comparing simultaneously the cohesiveness and the multiplexity of their neighborhood to a maximum entropy null model. For each pair of multilinks connecting the nodes i,k and j,s, the similarity is defined as:

$$S_{ik,js} = \varepsilon\sigma_{ijk} + (1-\varepsilon)\sigma_{ij/k} \tag{3.33}$$

This similarity is non-zero only between incident multilinks. The parameter $\varepsilon \in (0,1)$ can be tuned depending on the role assigned to the composition of the two incident multilinks with respect to their local neighborhood. Instead, $z \in (0,1)$ quantifies the role of multiplexity and represent the cost attributed to incident multilinks of different composition. $\sigma_{ijk} = z^{\beta_{ij,jk}}$ with $\beta_{ij,rs} = 1 - \frac{\sum_1^M m_{ij}^{[\alpha]} m_{rs}^{[\alpha]}}{M}$ evaluates the contribution of the two incident multilinks; while $\sigma_{ij/k}$ is a measure of the contribution due to the existence of other multilinks, joining node i and node j directly or by paths of length two excluding node k. z tunes the layer dependance of the multilink communities. A large value of z favors communities existing only in one layer or overlapping in different layers, while a smaller value of z allows for multilink communities of multilinks with different composition. If the multilinks between (i,k) and (j,k) have not even a link in a common layer $\beta_{ik,jk} = 1$, corresponding to the maximum cost for multiplexity. While if the two multilinks have same composition them $\beta_{ik,jk} = 0$ indicating no cost for this configuration. $\sigma_{ij/k}$ stays for the contribution of paths of length one (M_{ij}) and two $\widehat{M_{ijr}}$ between i and j passing through r with $r \neq k$:

$$\sigma_{ij/k} = \frac{1}{\mu}[M_{ij} + \sum_{r \neq k} \widehat{M_{ijr}}] \tag{3.34}$$

where $\mu = min(A_{ir}, A_{jr})$. M_{ij} is a sort of modularity which measures the relevance of the observed multilink and $\widehat{M_{ijr}}$ evaluates the significance of two non-trivial multilinks connecting respectively node i and node j to a common node $r \neq k$.

$$M_{ijr} = (A_{ij} - p_{ij}^{\vec{m}_{ij}}) z^{\beta_{ij,ij}} \delta(A_{ij}, 1) \tag{3.35}$$

$$\widehat{M_{ijr}} = (A_{ir}A_{jr} - p_{ir}^{\vec{m}_{ir} p_{jr} \vec{m}_{jr}}) z^{\beta_{ir,jr}} \delta(A_{ir}A_{jr}, 1) \tag{3.36}$$

where $\delta(x,y)$ is the the Kronecker delta (1 for $x = y$ and 0 otherwise); $z^{\beta_{ir,rs}}$ assigns a cost to the paths created using different layers; $\vec{m}_{jr}$ is the expectation of multilink, given by the probability $p_{rs}^{\vec{m}_{rs}}$. In ohter words, the parameter ε is used to tune the contribution to the similarity $S_{ij,jk}$ coming from the composition of the two incident multilinks and the local clustering of the multiplex network in proximity of the edge ijk. In particular, the smaller is ε, the larger is the contribution due to the local clustering of the multiplex network.
From the similarity matrix $S_{ik,js}$, it is possible to extract a dendrogram which puts in evidence the hierarchical structure of this clustering approach. The dendrogram contains information about the multiplex structure which cannot be obtained from the aggregated network. Then, the multilink communities are determined considering an appropriate score function. In the figure 3.8 is shown a multiplex network composed by two layers, where the links in blue correspond to one layer and the dark pink ones to another layer, in the upper part. In the middle there is a dedrogram f the multiplex network obtained from the multilink similarity. And, finally, in the lowest part of the figure the the partition of the multiplex network into three communities revealing that communities can be formed by a single (community a, b, c, d) or multiple layers (community d, e, f) and that the nodes communities are independent on the node activity (node d belongs to two community and is active in one layer, node g is belongs to one community and is active in one layer). This suggests that the mesoscale organization of multiplex networks has a rich mesoscale structure that is not captured by methods that aim at aggregating the information on few single layers.
In order to study weighted multiplex networks we can take into account two additional

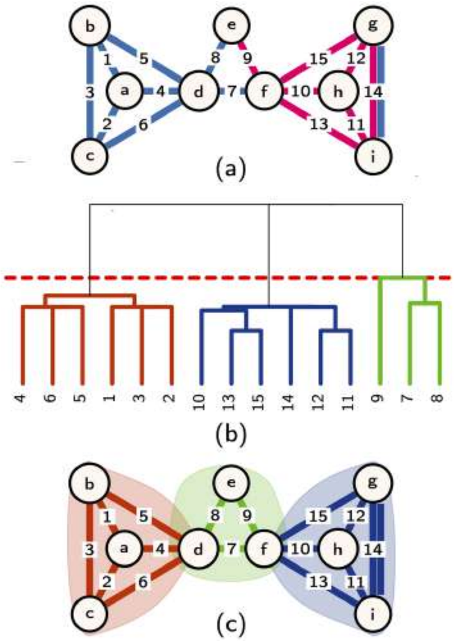

Fig. 3.8 A two layer multiplex and its partition into multilink communities. Figure reprinted figure from [99].

measures, for layer α and associated to multilinks $\vec{m}$ with $m\alpha > 0$, the **multistrengths** $s_{i,\alpha}^{\vec{m}}$ and the **inverse multiparticipation ratio** $Y_{i,\alpha}^{\vec{m}}$ [96]:

$$s_{i,\alpha}^{\vec{m}} = \sum_{j \neq i}^{N} a_{ij}^{\alpha} A_{ij}^{\vec{m}} \tag{3.37}$$

$$Y_{i,\alpha}^{\vec{m}} = \sum_{j=1}^{N} \left(\frac{a_{ij}^{\alpha} A_{ij}^{\vec{m}}}{\sum_r a_{ir}^{\alpha} A_{ir}^{\vec{m}}} \right) \tag{3.38}$$

3.4 Temporal Multiplex Networks

As expressed in the previous paragraphs many systems in nature, society and technology can be modeled as graphs of vertices connected by edges. The network structure, describing how the graph is wired is crucial to understand, to predict and to optimize the dynamics of dynamical systems. So far we assumed that the topology defining the network is static: the set of nodes and links do not change over time. However, many other real networks are far from static, their links being are not continuously active, they being created, destroyed, and rewired at some intrinsic time scales.Examples are represented by networks of communication via e-mail, text messages, or phone calls, where edges represent sequences of instantaneous or practically instantaneous contacts or the Internet [110, 137]. In other cases, edges are active for non-negligible periods of time such as in the case of proximity patterns of inpatients at hospitals which can be modeled by a graph where an edge between two individuals is active during the time interval they are at the same ward.

Like the network topology, also the temporal structure of edge activation affect the dynamics of systems which interact through the network, from disease contagion on the network of patients to information diffusion over the network. Discussing temporal networks means considering an additional dimension of analysis, where the times when edges are active are an explicit element of the representation. For these reasons, it is crucial to take into account also the temporal heterogeneity and ignoring this dimension, aggregating the contacts between vertices to (sometimes weighted) edges, means a lack of information about the temporal structure of contact patterns.

One of the key aspects of network theory is that the network structure strongly affect the dynamic processes which are mediated by edges and take place on top of it. This is particularly important for spreading processes where physical contact, social ties, or electronic connections are the means for diffusion. The temporal inhomogeneities, together with the fact that spreading processes have to follow the time ordering of events, have drastic effects on the dynamics of spreading on temporal graphs and this structure can also be exploited in controlling and preventing the spread. For such processes, the network structure affects the speed of spreading and the extent of diffusion through the network in accordance with short path lengths, the degree distribution, degree correlations, or community structure and correlations between tie strengths and network topology. The edges between vertices of temporal networks need not be transitive. For instance, considering the 3.9, in case of static network, directed or not, if A is directly connected to B and B is directly connected to C, then A is indirectly connected to C via a path over B. However,instead in the case of temporal network, if the edge (A,B) is active only at a later point in time than the edge (B,C), then A and C are disconnected, as nothing can propagate from A via B to C. Thus, the time ordering is crucial, the timings of connections and their correlations have effects that cannot be captured by a static network representation. Typical examples of temporal networks are: Person to person communication, Physical Proximity and one-ti-many information dissemination. The first one is represented by records of electronic one-to-one communication which are particularly suitable for the temporal network approach in the information spreading dynamics. These datasets are usually composed of lists of messages with their source, destination and point of time or time interval. Physical Proximity networks are composed by data about proximity patterns of human and about who is close to whom at what time. This kind of data are important for undertandi the spreading of

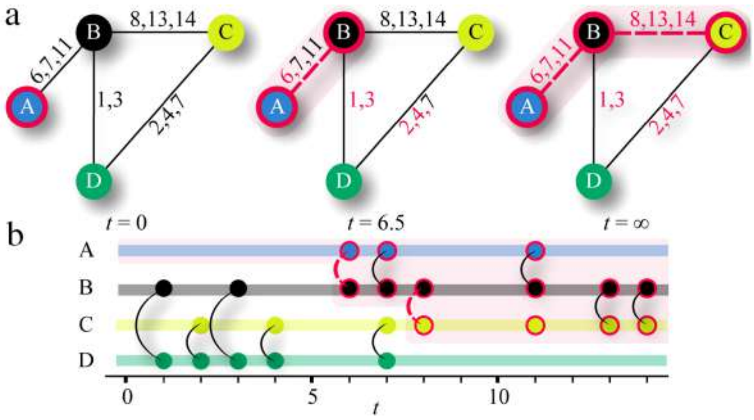

Fig. 3.9 Illustration of the reachability issue and the intransitivity of temporal networks. Reprinted figure from [72].

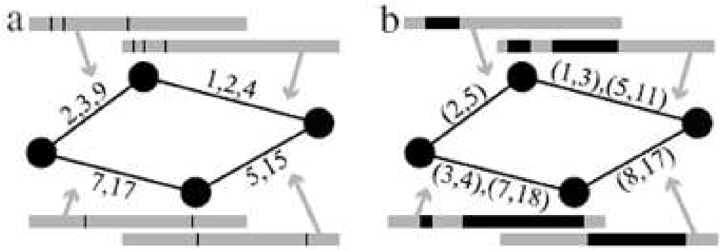

Fig. 3.10 Contact sequences and interval graph. Reprinted figure from [72].

airbone viruses or information. Nowadays several platforms that allows physical proximity measurements based on wearable badges equipped with radiofrequency identification devices (RFID) are available such as SocioPatterns [INSERIRE REF]. One to many Information dissemination or, in other words, the broadcast of information to anyone that might listen, in contrast to one-to-one communication which is another type of information spreading between humans that could benefit from a temporal network approach. The two fundamental temporal network representations are **contact sequences** and **interval graphs** (see Fig. 3.10) The first representation ((a) in Fig. 3.10) there is a set of N vertices V interacting with each other at certain times, and the durations of the interactions are negligible, as a consequence, the system can be represented by a set of C contacts, triples (i, j, t) where $i, j \in V$ and t denotes time. Equivalently, the system can be represented by V , a set of M edges (pairs of vertices) E , and, for $e \in E$, a non-empty set of times of contacts $T_e = \{t_1, ..., t_n\}$. The typical systems suitable to be represented as a contact sequence are sets of e-mails, phone calls, text messages, where the duration of the contact is less important. In the second representation ((b) in Fig. 3.10), interval graphs, the edges are not active over a set of times but rather over a set of intervals $T_e = \{(t_1, t_1^{'}), ..., (t_n, t_n^{'})\}$ where the parentheses indicate the periods of

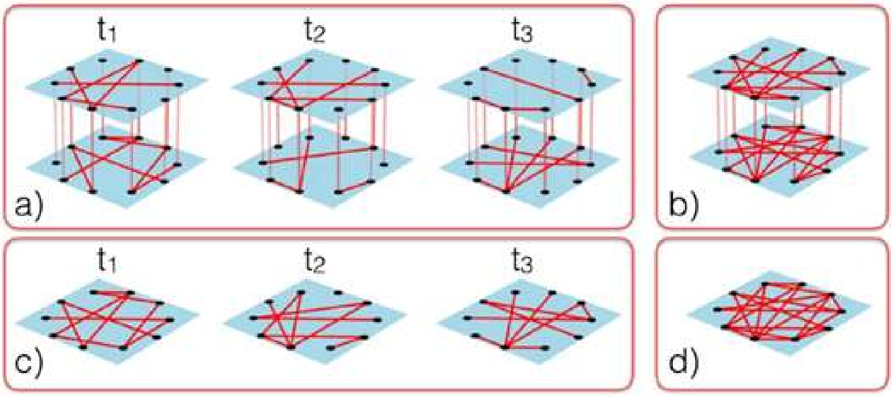

Fig. 3.11 Different observation levels of a Temporal Multiplex Network. Reprinted figure from [129].

activity. Examples of systems which can be naturally modelled as interval graphs include proximity networks (where a contact can represent that two individuals have been close to each other for some extent of time). It can be useful to define an index function of whether a pair of vertices is connected at a given time. This is the adjacency index $a(i,j,t)=1$ if i and j are connected at time t and $a(i,j,t)=0$ otherwise. Interactions in real world systems (such as in social networks) are stratified in multiple context and are subject to complex temporal dynamics [129, 66] and the systematic study of these two features has started very recently, thanks to the development of multiplex and time-varying networks. A temporal multiplex network $\mathrm{DM}=\mathrm{M}^1,...,\mathrm{M}^\mathrm{T}$ (see Fig. 3.11 (a)) is a sequence of multiplex networks, where each M^t with $t=1,...,T$ is a snapshot of the network at the time step t_i, within the time window of observation T [72], [129]. A multiplex network $\mathscr{M}$ is a network consisting of L layers $ł=\{1,...,L\}$ and N nodes $i=\{1,...,N\}$ with $|V|=N$ set of nodes. It is defined as a set of L networks (or layers) $G_\alpha=(V,E_\alpha)$ characterized by a set of nodes referred to vertices V, that is the same for each layer, whereas the set of links E changes according to the layer. Each network G_α is described by the adjacency matrix, denoted by A^α with elements a^α_{ij}, where $a^\alpha_{ij}=1$, if there is a link between i and j, otherwise $a^\alpha_{ij}=0$ [24]. Therefore, DM is defined by a set of quadruplets (i,j,t,l), indicating that a node $i\in V$ and a node $j\in V$ are connected at a time $t\in T$ in a layer $l\in L$ [129]. The static graph with an edge between i and j if and only if there is a contact between i and j is called the (time) aggregated graph (see Fig. 3.11 (b)); the mono-layer graph in which the multiplex dimension is aggregated is shown in Fig. 3.11 (c); the both mono layer and static aggregate graph is represented in 3.11 (d).

Chapter 4

Evolutionary Game Theory

Overview: In the previous chapters it was highlighted that the "connectedness" among elements within complex systems is fundamental to understand the evolutionary dynamics of complex dynamics and it was deepen how these depend strictly on two factors: the underlying structure with existing links and the implicit interdependence between the behaviour of an individual and that of other elements of the population. The first aspect makes it crucial the modeling through a multilayer network approach, whose characteristics were deepened in the previous chapter 3; the second is the study of the interconnection and the interdependence among behaviors through the Game Theory mathematical tool. The introduction of GT and, in particular EGT, is crucial also in the evolution of future ICT and it has already been used in synergy with edge computing and intelligence to shed light on aspects such as learning, cooperation and connections and showing how EGT can enhance the usage of the networking edge resources [11], in order to exploit collaboration for the creation of the so-called "collective edge intelligence". Evolutionary games application, acting as a reinforcement learning scheme, allows nodes with limited-rationality to select an initial strategy and apply it to a specific network, receiving a feedback (as a payoff) from the environment. After playing a game through many rounds, it is expected that nodes' behaviours will be completely adjusted to the dynamically changing environment, learning which is the most profitable behaviour for the whole system. The aim of this chapter is to introduce the definitions of the Classical Game Theory, then declining it the case of Evolutionary Game Theory (EGT). The main social dilemmas, their variants and the concepts of solution will be presented.

4.1 Traditional Game Theory

The classical Game Theory was born in 1920s thanks to John Von Neumann who developed a scientific strategic approach to be applied in the game of poker. Later, in 1944, together with Oskar Morgensten, he decided to write the first prototypical framework of game theory

“Theory of Games and Economic Behavior”, [141] where authors translated the human behaviours in conflict or cooperative situations into mathematical models and they defined the game as " any interaction between agents that is governed by a set of rules specifying the possible moves for each participant and a set of outcomes for each possible combination of moves.” In the early 1950s, one of the most important contributions came from the American mathematician John F. Nash, who introduced a simple but crucial concept the "Nash equilibrium", used for the study of negotiation between several subjects and giving the starting point for the application of models of game theory to the most disparate areas: from economics, political science or psychology for the study of behavior in conflict situations. Game Theory refer, therefore, to that branch of mathematics which analyzes conflict situations and searches for competitive or cooperative solutions through models, providing tools for the study of individual decisions in situations where there are interactions between two or more subjects. It is used to study those circumstances in which the outcome of an individual’s decision depends not only on the individual choice between different options, but also on the decisions taken by the individuals interacting with it: the choices of a subject may affect, therefore, on the achievable results by a rival and vice versa. The purpose of these theories is to use mathematics to describe and predict what will happen in a game as in a real-world situation. In addition to the study of games, these theories apply these games, theoretically formulated (strategic games), with the aim of analyzing real contexts, describing and predicting decision-makers behaviors in conflict situations. These studies have essentially two roles: the first one, positive, which consists in interpreting reality and trying to explain why, in specific contexts, a decision-maker acts in one way rather than in another; the second, prescriptive, which aims to determine which outcome will arise from the encounter between two, or more, players.

4.1.1 What is a game?

A game is a model of interaction between decision makers where each one plans his actions simultaneously. In each game there are [49]:

- A set of N participants, called players;
- Each player has at his disposal a set $A_i = a_{i1}, a_{i2}, ..., a_{in}$ of any possible actions or strategies;
- Together with each strategy, each player receives a payoff that numerically characterizes the player’s preference. Every player tends to maximise his payoff as much as

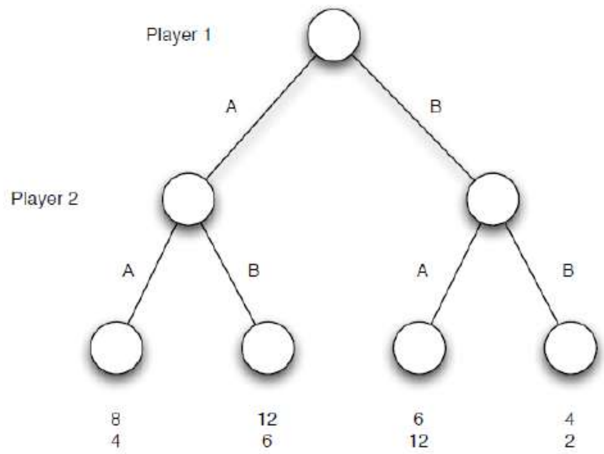

Fig. 4.1 Extensive form for dynamic games. Reprinted figure from [50].

possible. The payoff values are generally inserted into a payoff matrix, which describes the rules of the game

Games can be classified in single-stage (one-shot) games or repeated (iterated) games. In the first case, games are called static and players play simultaneously, choose their actions independently and make their choice only once, while, in the second ones, there are more rounds, representing a certain number of repetitions of some one-shot game. Due to the presence of many rounds players have to consider not only its current action but also its impact of future actions of other players (for instance through reputation mechanisms). In addition, by definition an iterated game is dynamic because a player can vary its strategy in accordance with the payoff obtained in the previous rounds. For static games, it is used the representation called normal form (through the payoff matrix) which specifies the list of players, their possible strategies and payoffs resulting at each possible choice of participants. For dynamic games it is needed a richer representation, called extensive form, where it is specified who moves and when, what players know before moving, what they can do when it's their turn and what are the payoffs at the end of the game. This form of representation can be depicted with a tree structure, as the example shown in the Fig.4.3. The top represents the initial move of a player and the two branches that descend from it indicate the two possible choices *A* or *B*. The node 2 represents the move played by the player 2, also it can choose between *A* and *B*, once again represented by two links that branch off from this node. This process leads to a final node that describes the end of the game; each final node is labeled with a numerical value that indicates the payoff obtained by the participants. In addition, games can be categorized according to the number of participants:

- Two-players, to this category belong symmetrical strategic games, with two players and two strategies.
- Multiplayer games, games with $n > 2$ participants.

In order to understand how players will behave, and choose their strategies we will focus on two-player game, but the reasoning can be applied to games with any number of players. Game Theory starts from some assumptions:

- the interacting decision makers are considered rational and they act with the aim to maximise their payoffs according to his predictions on the strategies adopted by the other player. This assumption combines the idea of maximising the payoff with the idea that each player is able to select the optimal strategy. These two ideas are both reasonable if experienced decision makers play a simple game but in complex games player can fail and make mistakes in the choice of the strategy, and it becomes interesting to see how players make mistakes and learn from playing the game how adjust their strategy.
- players know all the rules and the structure of the game, that is all the possible strategies and the related payoffs. This assumption is also applicable if we consider games with complete information but there are a lot of situations which can be modelled with games with incomplete information [50].

In fact, games can be further classified in:

- Games with perfect information, if all the players are aware of the possible actions and the correspondent payoffs for each antagonist. Therefore, players know in advance all the actions of others. Games of this type are sequential, so a participant's choice can actually be based on a full knowledge of the context.
- Full information games, if individuals have information about the context and choices of opponents but do not know all their possible strategies. Participants simultaneously decide their own move, in secret, and then play it simultaneously.
- Games with imperfect information, if at least one player does not have any information about the possible actions and the payoff received by opponents.

4.1.2 Best Response, Dominant Strategy and Nash Equilibrium

The **best response** is the best choice for a player, given his belief about the choice of the other player in a two-player game [50]. Analytically, if S is the strategy chosen by the first player (P_1), and T is the strategy chosen by the second player (P_2), in the payoff matrix there is an entry which corresponds to the pair (S,T). As a result, $P_1(S,T)$ and $P_2(S,T)$, are the payoffs obtained by the two players. Therefore, S for P_1 is a best response to a strategy T for P_2 if the payoff is at least equal to the payoff obtained by choosing another strategy $S^{'}$ paired with T:

$$P_1(S,T) \geq P_1(S^{'},T) \forall S' of Player 1 \tag{4.1}$$

Obviously, it is possible to give the symmetric definition for the player 2, and we will do the same also for the other following definitions. In addition, there are situations in which there may exist many strategies corresponding to the best response and this make difficult to predict which strategy will be chosen by Player 1. Hence, we can also define the strict best response, as follows:

$$P_1(S,T) > P_1(S^{'},T) \forall S' of Player 1 \tag{4.2}$$

There are other crucial concepts, related to the definition of best response, **dominant strategy**, defined as the best response to every strategy chosen by P_2, and strictly dominant strategy, defined as a strict best response to every strategy of P_2. The notion of a dominant strategy is slightly weaker than the strictly dominant one, since it can be equal to another strategy as the best choice against some opposing strategies, so there is no certainty about the strategy to be adopted.

In absence of dominant strategies, players are likely to choose strategies which represent best responses to each other or, in other words, supposing that each player chooses a strategy, the pair of strategies (S,T) is a **Nash equilibrium** (NE) if S is a best response to T, and vice versa T is the best response to S. Considering a two-player game with respective payoff matrices P_A and P_B, where A and B denote the two players. Indicating with $P_A(S,S^{'})$ the payoff of A when A plays S and B plays $S\prime$, this is the $(S,S^{'})$-entropy for P_A of the matrix P_A. A pair of strategy $(\tilde{S_A},\tilde{S_B})$ is a Nash equilibrium for a two-player game if no player can have a better payoff by changing his strategy from his equilibrium strategy to another strategy considering that his opponent keeps his equilibrium strategy. In terms of the payoffs matrices this means that:

$$P_A(S_A,\tilde{S_B}) \leq P(\tilde{S_A},\tilde{S_B}), \forall S_A; P_B(\tilde{S_A},S_B) \leq P(\tilde{S_A},\tilde{S_B}), \forall S_B \tag{4.3}$$

Thus, a strategy $\tilde{S_A}$ is a best response to a strategy S_B if:

$$P_A(S_A,S_B) \leq P(\tilde{S_A},S_B), \forall S_A \tag{4.4}$$

The concept of Nash Equilibrium provides a tool to find out the optimal outcome of a game, indeed a player has not any reason or incentive to deviate from his strategy after considering the other player's choice, because he will not receive a higher payoff, if the other player will not change his strategy. A game may have multiple Nash equilibria or none at all. Nash equilibrium can be interpreted as an equilibrium in beliefs, if each player believes that the other one will play a strategy which belongs to a Nash equilibrium, then also the other will choose the other strategy of the equilibrium. The Nash equilibria can be found in two ways: checking all the possible pairs of strategies and see if each one represents a pair of best responses to each other and calculating the best response of each player to every strategy chosen from the other player,and then find the strategies representing the mutual best responses to each other.

4.1.3 Pareto-Optimality and Social Optimality

It is interesting to classify the outcomes of a game not only according to the strategies or at equilibria, but also considering the concept of "social and common good" as a whole. To this purpose, a key concept is the **Pareto-optimality**, according to which the choice of strategies (one by each player) is Pareto-optimal if there is no other choice of strategies in which all players receive payoffs at least as high, and at least one player receives a strictly higher payoff. The basic concept of Pareto-optimality is that, even though both the players realise that there is a better solution, it is not possible to maintain it without a binding agreement between the two players. The second key concept is **social optimality** defined as follows: a choice of strategies is a socially op-timal if it maximises the sum of the players' payoffs. It is important to note how socially-optimal outcomes must be Pareto-optimal, so the Pareto-optimality is a necessary but not sufficient condition to have a social-optimality. An outcome Pareto-optimal implies that there would be a different outcome where all payoffs were at least the same and and one was larger, and this would be an outcome with a larger sum of payoffs. It is not a sufficient condition, since a Pareto-optimal outcome need not be also socially optimal.

4.2 Evolutionary Game Theory

Evolutionary Game Theory (EGT) applies the basic concepts of traditional Game Theory in those situation in which the assumption of rationality of decision-makers is relaxed and participants do not make explicit decisions. EGT is applied to model situations in which individuals can show different forms of behaviour (not only conscious choices), and to consider which forms of behaviour have the ability to emerge and persist within the population [50]. EGT has been applied most widely in the area of evolutionary biology and more recently also in social contexts. Evolutionary biology is based on the idea that genes determine observable characteristics of organisms, and its fitness in the considered environment [117]. The key concept of EGT is that many behaviours involve the interaction of multiple organisms within a population, and the success of any one of these organisms depends on how its behaviour interacts with that of others. As a consequence, the fitness of an individual organism cannot be measured in isolation but it has to be evaluated taking into account the whole population. Even if classical and evolutionary game theory differ radically in some basic assumptions aspects such as how they consider strategic interactions, there are some analogies between the two theories. The genetic features of an organism and the corresponding behaviours represent its strategy in a game, its fitness corresponds to payoff, and payoff will depend on the strategies (characteristics) of the interacting organisms. Also idea of equilibrium formulated by Nash, matches with the the concept of evolutionarily stable strategy (ESS) in EGT which is crucial to make predictions about the results of evolution on a population.

4.2.1 Fitness, Diversity, Selection and Replication

These evolutionary systems such as biological, social and economic ones are made up of entities of different nature, such as animals, genes, cells, behaviours, etc., characterized by some common properties: diversity, selection, and replication. **Diversity** is that entities in the system show dissimilarities affecting their individual fitness. **Fitness** is a measurable indicator determining how a population evolves, so that entities with higher fitness tend to persist in the population. The linkage between the fitness and the future population composition is the selection mechanism, which represents the trend to reduce the heterogeneity of the system, favouring the entities with higher fitness. Despite the selection mechanism, there are some other processes that generate and preserve a certain amount of diversity and heterogeneity in systems. For instance in biology, the diversity is generated and preserved by genetic mutations, in economic systems by innovations, in ICT systems or social networks by the flow of information and data through the network, which trigger modifications in the behaviours. Strategies (which may be seen as behavioural phenotypes) are selected on the basis of their payoff, that is the relative frequency of strategies which obtained higher payoffs in the population will increase at the expense of those which obtained lower payoffs. **Replication** can be considered as a mechanism which preserve the properties of the entities in the system; for instance, In biological systems, replication is constituted by genetic transmission, while in social systems, replication is represented by the imitation in the social learning processes.

4.2.2 Evolutionarily Stable Strategy

The study of dynamic systems begins with the identification of their stable states, not considering the dynamics of the system explicitly, but only its rest points. In order to determine these stable states, the Evolutionarily Stable Strategy (ESS) is an analogous notion of Nash equilibrium in traditional game theory. It was proposed by by J. M. Smith and R. Price in 1973 and it represents the most important concept in EGT. ESS can be defined as a strategy that tends to persist once it is prevalent in a population. In other words, a strategy is evolutionarily stable if a any small group of invaders using a different strategy than the population will eventually die off over multiple generations [50]. For instance, in biological terms, these invaders could be represented as mutants born into the population with a different behaviour, or migrants joining the population. The definition of ESS starts from some assumption: it is considered a system composed by a single infinite population of individual who play a two-players sysmmetric game. futhermore, it considers only a population where all individuals play the same strategy invaded by only one kind of mutant strategy at a time. Indeed, this assumption of one single infinite population represents a mean-field approximation used to match the average payoff actually obtained by a population with the expected value of a probability distribution of payoffs. To better capture the concept of ESS in terms of payoff, we consider a population using a strategy S and a small group of invaders using a strategy T, with a strictly lower fitness in comparison with the strategy of the majority of users. As fitness means reproductive success, the population of invaders will decrease over time and die off in the evolutionary process. The fundamental concepts related to EGT are the following:

- The fitness of an organism in a population is the expected payoff it receives from an interaction with a random member of the population.
- A strategy T invades a strategy S at a certain level δ, for some small positive number δ, if a delta fraction of the underlying population uses T and a $1...\delta$ fraction of the underlying population uses S.
- A strategy S is evolutionarily stable if there is a (small) positive number γ, such that when any other strategy T invades S at any level $\delta < \gamma$, the fitness of an organism playing S is strictly greater than the fitness of an organism playing T.

Therefore, the concept of an evolutionarily stable strategy can be viewed as a refinement of the concept of a Nash equilibrium: the set of evolutionarily stable strategies S is a subset of the set of strategies S for which (S,S) is a Nash equilibrium. It could be said that if a strategy S is evolutionarily stable, then (S,S) is a Nash equilibrium". The opposite direction does not hold:

it is possible that (S,S) is a Nash equilibrium, but S is not evolutionarily stable. For what concern the concept of strict Nash equilibrium (when the players use the same strategy which is the unique best response) is could be viewed as a refinement of evolutionary stability: if (S,S) is a strict Nash equilibrium, then S is evolutionarily stable. Furthermore, it is interesting to consider how, despite the extremely close similarities between the conclusions of ESS and Nash equilibrium, they are built on completely different underlying concepts. From one hand, in a Nash equilibrium, we consider players choosing mutual best responses to each other's strategy. So it demands on the ability of the players to choose optimally and to coordinate on strategies that are best responses to each other. On the other hand, Evolutionary stability, supposes no intelligence or coordination from players: strategies are naturally placed into the players, because their behaviour is encoded in their genes. ESS increases the fitness of the more successful strategies with a higher reproductive success in the selection process.

4.2.3 Evolutionary Dynamics

Evolutionary dynamics were defined by Nowak [106] as the mathematical formulation of evolutionary processes which population to change. Natural selection is an example of these processes, in which genotypes (as strategies) with higher fitness tend to become more common, while lower-fitness genotypes tend to disappear and, then mutation reintroduce a certain grade of heterogeneity into the population. Similar processes represent cultural evolution and social learning where people tend to imitate strategies and behaviours associated to higher payoffs. For these reasons, EGT can be seen as a combination between game theory (in the mathematical formulation) and evolutionary dynamics: considering a population of agents, each of them choose a strategy; they interact with each other and earn payoff; the concept of payoff in EGT is translated to fitness and the frequency of strategies' adoption changes accordingly with them: higher-payoff strategies tend to become more common, whereas lower-payoff strategies tend to disappear. At the foundation of the evolutionary dynamics there are the so-called replicator equations, introduced by Taylor an Jonker in 1978 [132]. Denoting with x the state of the population, that is the distribution of strategy frequencies, and with x_i the differentiable functions of time t, which means to assume that the population is infinitely large, we can now postulate a law of motion for $x(t)$. We also assume that individual meet randomly and are involved in a game characterized by a payoff matrix P, such that $(W_x)_i$ is the expected payoff for agent i using strategy S_i and $x^T W_x$ is the average payoff for the population in the state x. Considering the payoff as the correspondent concept of fitness and that the growth rate of individuals adopting a strategy s_i is proportional to its payoff, the **replicator equation** is defined as follows [71]:

$$\dot{x_i} = x_i[(W_x)_i - x^T W_x] \tag{4.5}$$

where $\dot{x_i}$ is the derivative of x_i , and the $x^T W_x$ exists in relation to the constraint: $\sum_i (x_i) = 1$. The equation 4.5 is the mathematical representation of the principle of natural selection, in accordance with which strategies with higher fitness spread more efficiently in a population. States $x_1 = 1$ and $x_j = 0\ \forall i \neq j$ are solutions of the equation and they are defined absorbing states which play a key role in the system dynamics without mutations. For what concern the solutions of the replicator dynamics equation, they represent equilibria or rest points indicating the frequency distributions which make the second member of the equation equal to zero: $x_i = 0$ or $(W_x)_i = x^T W_x = 0, \forall i = 1,...,n.$ These solutions are the mixed strategy Nash equilibria of the game and Nash equilibria, themselves, are stable rest points. Therefore, the replicator equations describe the evolutionary dynamics which lead the players to the NE, or ESS. Each equilibrium has different attraction which makes the difference in their selection when there are more than an equilibrium. The hypotheses underlying the replicator equation are the following:

- population in infinitely large;
- Individuals meet randomly or play against every other one, such that the payoff of strategy S_i is proportional to the payoff averaged over the current population state x.
- There are no mutations such that the increasing or decreasing in frequency of strategies depends only on reproduction mechanism.
- The variation of the population is proportional to the payoff difference.

The first two hypotheses are fundamental in order to derive the replicator equation, replacing the fitness of a strategy using its mean value, with the population described in terms of frequencies. In particular, the second assumption is related to temporal and spatial constraints of interactions, which requires another approximation for representing the fitness of a strategy in a population, as the expected value of fitness is no longer valid. For what concern the third constraint mutation could be included producing the so-called replicator-mutator equation [108]; the fourth assumption is the definition of **replicator dynamics**. When the hypothesis of linearity is not included the generalised replicator equation is the following:

$$\dot{x_i} = x_i[(W_i)_x - x^T W_x] \tag{4.6}$$

Replicator dynamics are the rules in accordance to which player update their strategies through the round of the game. These rules are classified in Innovative and Non-Innovative in relation to their ability to introduce new strategies into the population or reintroduce the extinct ones. Based on the speed with which they trigger the change of strategies the rules can be classified into payoff monotonous or non-monotonous. Examples of Innovative dynamics are:

- Best Response dynamics: In a population a small percentage of players update their strategies, choosing the best response $BR(x)$ to the average x strategy of the entire population. This approach starts from the assumption that players are smart enough to assess the current state of the entire population and respond optimally.
- Logit dynamics: constitute a generalization of Best Response dynamics in the case of "limited rationality" (Smoothed Best Response). In accordance with these laws, players update their strategies respecting a parameter β, which takes into account the level of rationality and knowledge of players, and the state of the system, or strategies played until now. The logit update rule can be seen as a classic best response "noisy" rule. A small value of β represents a situation in which players are subject to a loud noise or have a very limited knowledge of the game and, consequently, choose the strategy to play randomly; instead, a large value of β represents a situation where participants are quite sure to play their best response.
- Fermi's rule: At the start of the game, considering as an example a case of 2-player 2-strategy game, the player x plays a strategy S_x while the player y a strategy S_y. The evolution of the two strategies takes place by comparing the payoffs π_x that each player accumulates at the end of a pair interaction with their neighbors. Next, player x tries to impose its S_x strategy on player y with the probability $W(S_x \rightarrow S_y))$ defined by:

$$W(S_x \rightarrow S_y) = \frac{1}{1 + exp[\frac{\pi_x - \pi_y}{k}]} \tag{4.7}$$

Where k quantifies the noise amplitude and its inverse is defined as selection intensities. If $k \rightarrow 0$ and $\pi_x > \pi_y$ x will be able to impose its strategy on y.

4.2.4 Social Dilemmas for studying the Emergence of Cooperation

EGT is often applied in order to understand the emergence of cooperation in different situations, in particular among human beings. Cooperation in a competitive world could be seen in contrast with the natural selection mechanism [112]. In the analysis of the evolution of

Table 4.1 Payoff matrix.

	C (Cooperation)	**D (Defection)**
C (Cooperation)	R	S
D (Defection)	T	P

cooperation it is useful to exploit the so-called social dilemmas [75, 114, 113], which are two-players and two-strategies games. Social dilemmas are situations in which collective interests are at odds with private one. In fact, in social dilemmas there is a contraposition between what is good for the entire population and what is the best strategy for the individual. The population does best if individuals cooperate, but for each individual there is a temptation to defect. Cooperation is an act where individuals can contribute something, at a cost to themselves, to provide a benefit for others. In EGT, cost and benefit are measured in terms of reproductive success. In other words, social dilemmas represent the tension between the benefit of the individual and the social common good. The two possible strategies are cooperation (C) or defection (D), where cooperating means contributing to the benefit of the whole population paying a cost and defection means being selfish and not paying any cost and relying on the cooperation of other player [47, 38]. There are different models of social dilemmas, the iterated forms of Prisoner's Dilemma game (PD), the Snowdrift game (SD), the Stag-Hunt game (SH) and the Harmony game (HG). These dilemmas are two-strategies games, with different features, as specified in the payoff matrix and players can choose between to cooperate (C) or to defect (D): Where R represents the reward gained by a co-operator playing against another co-operator, S is the sucker payoff obtained by a co-operator that plays against a defector, T is the temptation payoff obtained by a defector when he plays against a co-operator, and P represents the punishment for the mutual defection. The selection of the matrix parameters enables the definition of several games according to their evolutionary stability [114].

If $R > S$ and $R > T > P$ the game is the HG where cooperation is its dominant strategy, results the most cooperative game. The opposite situation, with $T > R > P > S$, is represented by the PD which is the most challenging and stringent social dilemma in terms of cooperation where defection dominates cooperation; $T > R > S > P$ yields the SD that is an anti-coordination game characterised by a stable equilibrium in mixed populations. Thus, we observe the coexistence of both strategies at equilibrium, cooperation and defection [INSERIRE FIGURA] finally $R > T > P > S$ corresponds to the SH [90] which is characterized by an unstable evolutionary equilibrium with mixed populations. As in the SD case, we have the coexistence of both strategies, even if the density of cooperation is on average lower than SD [114]. .

The payoff matrices of the four games are illustrated in the following tables:

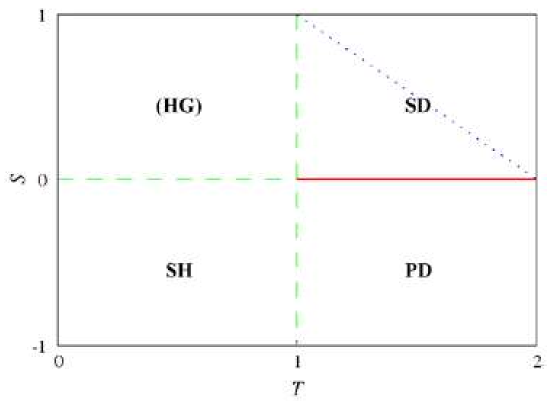

Fig. 4.2 Representation of the stag-hunt (SH), the prisoner's dilemma (PD) and the snowdrift (SD) game on the two-dimensional T-S plane. The upper left quadrant represents the so-called harmony game (HG). The latter, however, does not constitute a social dilemma because there cooperation is always the winning strategy. The dashed green lines denotes the borders between games, while the diagonal blue the cost-to-benefit ratio of the snowdrift game, while the thick red line shows the span of the weak prisoner's dilemma game having $R = 1$ and $P = S = 0$. Reprinted figure from Ref [114]

Table 4.2 Payoff matrix of the Prisoner's Dilemma

	C (Cooperation)	**D (Defection)**
C (Cooperation)	$b-c$	$-c$
D (Defection)	b	0

Table 4.3 Payoff matrix of the Snowdrift Game

	C (Cooperation)	**D (Defection)**
C (Cooperation)	$b-c/2$	$b-c$
D (Defection)	b	0

Table 4.4 Payoff matrix of the Stag-Hunt Game

	C (Cooperation)	**D (Defection)**
C (Cooperation)	$2b-c$	$-c$
D (Defection)	b	0

Table 4.5 Payoff matrix of the Harmony Game

	C (Cooperation)	**D (Defection)**
C (Cooperation)	$b-c$	b
D (Defection)	$-c$	0

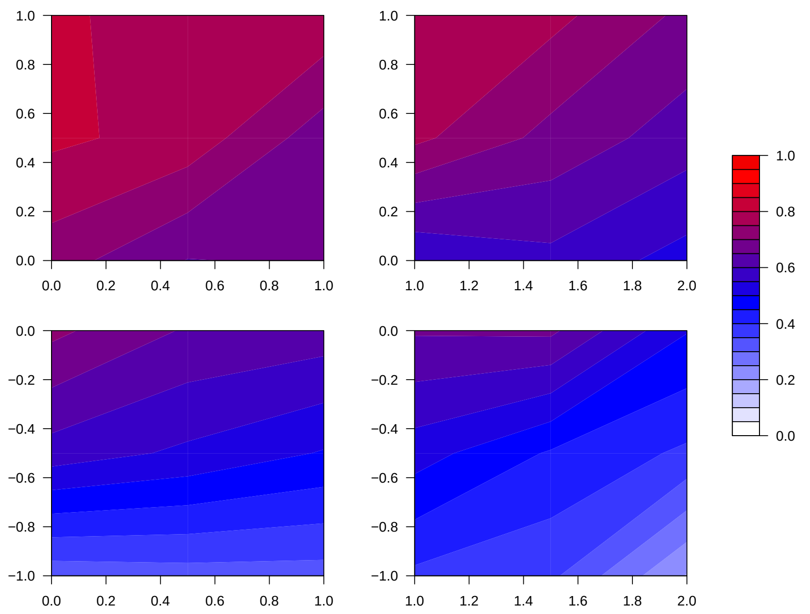

Fig. 4.3 Density of cooperators in the T-S plane, considering the different social dilemmas: HG (upper-left), (upper-right), SH (lower-left), and PD (lower-right).

4.2.5 Parameters for the emergence of cooperation in Multiplex Evolutionary Game Theory

Cooperation produces a conflict between the benefit of the single decision-maker and that one of the whole population. The reason why individuals do something for someone else, although there is often a low probability for direct reciprocity or reward is that actions are contagious. Only by studying the interactions inside the population it is possible to shed light on the hidden pattern which lead to cooperation. In fact, cooperation may introduce assortative interactions among decision-makers, transforming it to the most profitable strategy [47]. Among human beings, there are several mechanism at the basis of the evolution of cooperation, related to kin selection, direct reciprocity, indirect reciprocity, spatial selection and multilevel selection.

- Direct reciprocity is related to a cost of cooperating in order to obtain a gain in the near future.
- Indirect reciprocity involves the dependence of an individual's actions from the previous behaviours of the others.
- Spatial selection is linked with interactions and clusters of cooperators.

- Multilevel selection refers to competition existing between groups and between individuals.

The are other mechanisms proposed by Rand and Nowak:

- strong reciprocity refers to two individuals who reward cooperation and punish selfishness even if the interactions are anonymous and without promises of future benefits.
- upstream reciprocity refers to the mechanism whereby an individual who has just received help is more likely to help others.
- parochial altruism according to which an individual is more likely to help the members of the group to which he belongs than those of another group.

In addition to these mechanisms, the actions of networked decision-makers could be affected by a huge amount of other factors, among them one of the most important is the **homophily**. Homophily is the principle that similarity breeds connection. In nature, this concept generate interesting behaviours, giving shape to relationships and impacting on information sharing, influence dynamics and so on. Following the tendency to relate with similar individual, contact between similar individuals occurs at higher rater compared with interactions among dissimilar. In terms of network theory, this indicates that the attributes of vertices correlate across edges and it is known as **assortative mixing**. The concept of homophily is important in the dynamics of collective action and critical mass mobilization. Furthermore, it is crucial to distinguish between homophily, social dependence and social influence. Homophily means that similar nodes are more likely to contact. Social dependence means that nodes exchange resources in order to satisfy their goals. Social influence means that nodes which interact become more similar. The concept of homophily alone is not able to explain why individuals decide to connect or choose strategy when interact with others. For this reason, it becomes crucial to consider multiple types of relationships between nodes, known as multiplexity. As we have seen in 3 the multiplexity makes it possible to include several kind of interactions and relationships, exploring and unveiling how the different ties in the various layers can impact on the diffusion of behaviours and the emergence of collective phenomena within a population. It is useful also taking into account other parameters such as the **Critical Mass**, which refers to the minimum number able to arise a new behaviour and trigger a collective action within a population. In order to analyse the role of the connectedness and of the structural patterns on the emegenge of collective phenomena it is essential also considering the coupling among the different layers of the multiplex structure through the **communicabiliy function**.
Critical mass is defined as the minimum coalition $min(n)$, such that if actors organize into

coalitions of size equal to n, at least n people will prefer mutual cooperation to defection, and it is calculated as follows:

$$min(n) s.t. \{\sum_{i=1}^{N} H(R_i - T_i)\} \geq n \tag{4.8}$$

where n is the dimension of the overall population and $min(n)$ is the minimum coalition size which depends on the Heaviside function of the difference between Reward R_i and Temptation payoffs T_i respectively, evaluated considering different kind of games. In this respect it is useful considering that the most central nodes in the network are also the most influential, which can more easily condition the behaviours of their neighbouring nodes.
The homophily measure extended to the multiplex structure is defined through the Homophily matrix H^{α}, where each element h_{xy}^{α} represents the homophily measure between two nodes x and y in the layer α, calculated as:

$$h_{xy}^{\alpha} = \frac{1}{1 + \delta_{xy}^{\alpha}} \tag{4.9}$$

with δ_{xy} measuring the homophily difference between two nodes x and y.

The communicability function quantifies the number of possible routes that two nodes have to communicate with each other. The communicability between two nodes x and y in a multiplex is given by a weighted sum of all walks from x to y as follows:

$$G_{xy} = 1 + \mathscr{M} + \frac{\mathscr{M}^2}{2} = \sum_{k=0}^{\infty} \frac{\mathscr{M}^k}{k!} = [exp(Z_L + C_{LL})]_{xy} \tag{4.10}$$

where k is the length of walks between two generic nodes x and y; the walks of k length in the multiplex are given by the different entries of $\mathscr{M}^k$; Z_L represents the Hadamard product between the homophily matrices and the adjacency matrices of the multiplex, related to the different L layers; C_{LL} is a matrix describing the interlayer interaction.

Chapter 5

Epidemic Models

Overview: In a 6G communication scenario, treated as a complex relational ecosystem, we are interested in detecting emerging behaviours, determined by non-trivial networks of interactions. Thus, we start from multiplexity of networked users, leveraging the heterogeneity, homophily and awareness which represent unexplored innovative bio-inspired perspectives, typical of the complex systems and complex networks theory applied to various scientific fields from biology to telecommunication. In particular, it is crucial the interplay between awareness and spreading processes in fact, the more the networked individuals are aware about the spreading content, the more they may be able to adopt strategies to quickly disseminate or slow diffusion. It has been found the role of online social platforms and of the nature of social ties in spreading beliefs, habits and information, emotions and rumors, through the so-called social contagion, which spread as inter-personally as a epidemic disease [110, 124, 122]. In this chapter, it is merely presented some of the basic elements and notation generally used in the modeling of epidemic phenomena in order to provide the necessary conceptual toolbox needed in the following chapters. In particular, it is focused the importance to take into account also the aspects of heterogeneity and coevolution of different spreading phenomena in multiplex networks.

5.1 Classical models of epidemic spreading

A pivotal concept of epidemic models is that the considered population can be divided into different groups (or compartments) in accordance with their stage of the disease. Susceptibles (denoted by S) are those who can contract the infection, infectious (denoted by I) those who contracted the infection and are contagious and recovered (denoted by R) those who are removed from the propagation process, either because they have recovered from the disease or because they have died. In addition to these, other compartments can be included in order to consider other possible states, such as immune individuals [137, 110].

The aim of epidemic models is to describe the dynamical evolution of contagion process within a population, in order to understand the evolution of the number of infected individuals as a function of time it is useful to analyse the individual transition processes governing the shifting of individuals from one state to another one. The simplest way consists in considering the whole system's population as fixed, composed by N individuals without migrations or births.
The first model is the SIS which is two-state as only two transitions are possibles. The first one $S \Rrightarrow I$ takes place when a susceptible individual has contacts with a infected one and becomes infected himself. The second transition is $I \Rrightarrow S$ takes happens when the infectious individual recovers from the disease and returns to the compartment of susceptible individuals. This simple model starts from the assumption that the disease does not confer the immunity and individuals can be infected over and over again. Analysing the long time regime, the SIS model can reach a stationary state, defined the endemic state, characterized by a constant (on average) fraction of infected individuals.
The second model is represented by the SIR where the transition $I \Rrightarrow S$ of the SIS is replaced with $I \Rrightarrow R$, which takes place when an infected individual recovers from a disease and acquires a permanent immunity, or is removed from the population. In the long time regime, the number of infected individuals tends to zero always. While the $I \Rrightarrow S$ and $I \Rrightarrow R$ occurs spontaneously after a time interval spent fighting the disease or taking medical treatments, and it not depends on interactions among individuals; the $S \Rrightarrow I$ occurs due to the contacts between a susceptible individual with an infected one. For this reason, the pattern of interaction among individuals becomes crucial to understand the specific features of transitions. In a simplistic model scheme the probability of transition is assumed constant. In a discrete time formulation, the recovered probability μ is defined such that an individual will recover at any time step. In a continuous-time formulation, assuming a Poisson process μ is the rate (probability per unit time) and the probability to remain infected for a time tau follows an exponential distribution $P_{inf}(\tau) = \mu e^{(-\mu\tau)}$ with an average infection rate $< \tau >= \mu^{-1}$. The Poisson assumption for the processes of infection and recovery leads to a Markovian description of epidemic models. The definition of the probability of the transition $S \Rrightarrow I$ depends on many factors, such as on the nature of human interactions. The most simple approach considers that individuals interact randomly with each other, in this way the larger is the the number of infectious individuals among an individual's contacts, the higher the probability of transmission of the infection. α describes the probability for a susceptible individual to contract the infection in a single time step. In the continuous time α is defined as a rate $\alpha = \bar{\beta}\frac{N_I}{N}$ where $\bar{\beta}$ depends on the particular considered disease and on the interactions patterns of population, N_I is the number of infected individuals; $\bar{\beta}$ is often split

in two terms βk with β is the rate of infection per effective contacts and k is the number of contacts.
The above mentioned models can be rephrased as a reaction-diffusion process, following this approaches individuals can be seen as different kinds of particles which evolve according to interaction rules, defining each transition by appropriate reaction rates. In accordance with the reaction-diffusion formalism we can describe the SIS by the following reactions:

$$S+I \xrightarrow{\beta} 2I \tag{5.1}$$

$$I \xrightarrow{\mu} S \tag{5.2}$$

where β is the infection rate and μ is the recovery rate. The SIR model is characterized by the reaction:

$$S+I \xrightarrow{\beta} 2I \tag{5.3}$$

$$I \xrightarrow{\mu} R \tag{5.4}$$

The SIR process will asymptotically die after affecting a given fraction of population.
Other more realistic epidemic model can be defined analogously to the SIS and the SIR. the susceptible-infected-recovered-susceptible (SIRS) model is an epidemic model incorporates a temporal immunity:

$$R \xrightarrow{\eta} S \tag{5.5}$$

With η is the rate with which a recovered individual lose his/her immunity, making him/her susceptible again.
Instead, the SEIR model is a variation of the SIR with the inclusion of the exposed (E) state, where individuals have been infected but they cannot transmit it yet. Its reaction-diffusion notation is the following:

$$S+I \xrightarrow{\beta} E+I \tag{5.6}$$

$$E \xrightarrow{\gamma} I \tag{5.7}$$

$$I \xrightarrow{\mu} R \tag{5.8}$$

The classic epidemic dynamic theories where based on taking the continuous-time limit of difference equations for the evolution of the average number of individuals in each compartment. This deterministic approach starts from the assumption that the individuals in the population are well mixed and interact with each other completely at randomly; therefore, each individual in a compartment is treated at the same way from the others in that same compartment. Starting from this perspective, full information about the state of the epidemics

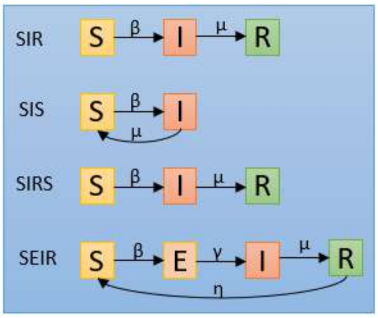

Fig. 5.1 Diagrammatic representation of different epidemic models in terms of reaction-diffusion processes. Boxes stand for different compartments, while the arrows represent transitions between them.

is encoded in the total number N^{α} of individuals in a compartment α or, analogously, the density $\rho^{\alpha} = \frac{N^{\alpha}}{N}$ where N is the whole population size. The time evolution of the epidemics is described by deterministic differential equations, showing that the average change of each compartment density is given by the product of the force of infection times and the average population density, for SIR and SIS we have:

$$\frac{d\rho^I}{dt} = \beta\rho^I\rho^S - \mu\rho^I \tag{5.9}$$

$$\frac{d\rho^S}{dt} = -\beta\rho^I\rho^S + \chi\rho^I \tag{5.10}$$

where $\chi = \mu$ in the case of SIS model and $\chi = 0$ for the SIR model and the forse of infection is $\alpha = \beta\rho^I$. The normalization condition for SIR is $\rho^R = 1 - \rho^S - \rho^I$ and for the SIS model $rho^S = 1 - \rho^I$. Cosinderig that at the early stage of the epidemic, it is generally valid the limit $\rho^I \simeq 0$ we have:

$$\frac{d\rho^I}{dt} = (\beta - \mu)\rho^I \tag{5.11}$$

with solutions:

$$\rho^I(t) \simeq rho^I(0)e^{(\beta-\mu)t} \tag{5.12}$$

which represents a key pillar concept of the classic epidemic theory and that the number of infectious individuals grows exponentially if:

$$\beta - \mu > 0 \Rightarrow R_0 = \frac{\beta}{\mu} > 1 \tag{5.13}$$

where R_0 is the average number of secondary infections caused by a primary case in a population of susceptibles. Hence, the concept of epidemic **threshold**: if $R_0 > 1$ a single

infected individual generates on average more than one secondary infectious and, therefore, a infective agent can cause an outbreak of a finite relative size (in SIR-like models) or lead to a steady state with a finite average density of infected individuals, corresponding to an endemic state (in SIS-like models). If $R_0 < 1$ the size of epidemics is small in SIR-like models or leads to a steady state with all individuals healthy in SIS-like models. The concept of threshold, expressed as a function of the rates of the different transitions describing the model, is common to all epidemic models. This classic approach is deterministic and assumes random and homogeneous mixing where each members within the same compartment is treated similarly. However, in reality belongs to the his/her own social contact network which diseases propagate, usually differing from that of other members in a group or compartment. In the case of homogeneous contact network where each member has the same number $< k >$ of contacts the reproduction number we have $R_0 =< k > \frac{\beta}{\mu}$. The concept of epidemic threshold is a concept similar to the phase transition in non equilibrium systems. It is an abrupt change in the state of a system, characterized by qualitatively different properties, and that is experienced varying a given control parameter. The transition is characterized by the parameter ρ which is nonzero in one state and equal to zero in the other one. The change of state occurs in correspondence of a particular value of the control parameter, the transition point λ_c, for $\lambda > \lambda_c$ we have $\rho > 0$, for $\lambda \leq \lambda_c$ $\rho = 0$. Around λ_c the order parameter takes a power-law form $\rho_\lambda \sim (\lambda - \lambda_c)^{\beta_c}$ defining the critical exponent β_c.
The homogeneous assumption considered in this section to evaluate the basic epidemic processes may be not adequate in many real-world situations where individuals show very heterogeneous contacts or are in contact with only a small part of the population, these aspects may have different relevance in the spreading phenomena considered. In addition, a wide range of social and biological contagion processes requires a knowledge about the contact pattern structure of individuals, also because most real world systems present very complex connectivity patterns characterized by large-scale heterogeneities.

5.1.1 The role of heterogeneity and interdependence on epidemic spreading processes

The classical models considered in the previous sections can be enhanced and generalized in order to provide a more realistic description of the diffusion phenomena, it could be useful to introduce additional compartments or allowing new transitions between the several compartments. These modification can be studied analytically or retrieved empirically and may alter the evolution of epidemic on networks. For instance, in real human disease epidemics, often, the assumption that the structure of contacts does not depend on the progression of the contagion is often unrealistic. In fact, the human behaviours tend to change accordingly to the influence of the spreading processes. The induced modifications can depend on several aspects, as different kind of information may influence the behavioural choice: in some cases the decisions are taken in accordance with the epidemic state; in other cases the choices are belief-based, based on the awareness or the risk perception which can be not dependent from the actual disease diffusion. Furthermore, the changes in behaviours may be of different kind, affecting the individual's state (for instance through vaccination) or the contacts' structure (i.e. cancelling connections or creating new ones).

Another crucial aspect is that, differently from the basic modeling scheme, it could be interesting considering the evolution of multiple epidemic processes in competition on top of the same network, which represent a crucial scenario for studying real situations. These epidemic processes are represented certainly by infectious diseases, which represent the main focus of these theories, however the contagion metaphor is applicable in several other domains, in particular in the social science field. The spreading of information, the propagation of rumors, the adoption of behaviours are phenomena where the state of individuals are influences by the interactions among them. Through the social contacts, these epidemic processes can give rise to epidemic like outbreaks like fads or information cascades, viral information diffusion online. This is a key element in most social networks, where it is almost impossible to disentangle the agents cognitive processes shaping the network evolution and their perception and awareness of the contagion processes. These phenomena can be defined as complex or social contagion, detectable empirically thanks to the unprecedented abundance of digital fingerprints, as data in online social platforms [69]. It makes necessary new theoretical approaches to measure, model, interpret and predict these phenomena which enhance the classical models for disease epidemics. In fact, the transmission of information, beliefs or behaviours involves the intentionality of individuals is relevant and it is influenced by cognitive and psychological aspects. The introduction of these ingredients makes it possible analysing others spreading phenomena attributable to social contagion like habits or behaviours which gives rise to collective phenomena such as in the case of obesity, smoking, happiness or distress [57].

The final aim consists not only in understanding epidemic processes and predict their behavior but also control their dynamics. In this sense, it is crucial investigating how coevolution of spreading phenomena and feedback mechanisms affect the ability to control these processes. The interdependence is a crucial aspect in diffusion and spreading processes. Networks shed light on a wide number of interdependencies ranging from logical to infrastructural ones. Interdependence is a major issue, for instance considering the spreading of information in communication networks which is based on physical proximity contact pattern of individuals

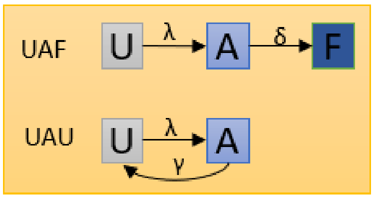

Fig. 5.2 Diagrammatic representation of awareness diffusion models in terms of reaction-diffusion processes. Boxes stand for different compartments, while the arrows represent transitions between them

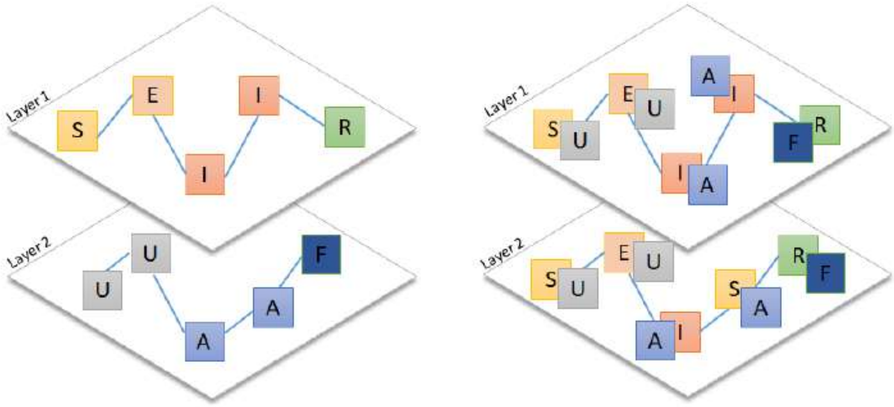

Fig. 5.3 Schematic example of the coevolution of epidemic and awareness spreading on a multiplex Network. In (a) the two processes is considered separately in different layers, while in (b) it is considered the coevolution in the whole multiplex network.

or of the flows and traffic of mobility infrastructure. This makes it necessary the introduction of interdependent networks, for instance in the case of information processes where different types of social communication networks (phone, real-world, digital) coexist it is useful rescuing on multilayer or multiplex networks.

5.2 The dynamical interplay between awareness and epidemic spreading in multiplex networks

As explained in the Chapter **??** many real complex systems are composed of several interrelated layers of networks. In particular, multiplex networks represent the natural way to describe social interactions that occur at different contexts or in different categories. The different layers can support several dynamical processes, for instance in online social networks individuals can exchange information, while in the physical network they have contacts that can carry on the diffusion of diseases. The dynamics of exchanging information

and of moving attention around a topic have an impact on the co-evolution of epidemic spreading and awareness. In order to explore the complexity in these emerging dynamics of the co-evolving and interdependent spreading processes, it is crucial to include the concept of (complex) social contagion which, as explained in section **??** based on epidemiological models [110], and it finds applications in network science, social behavioural analysis, misinformation diffusion, infectious disease and emotions spreading The awareness has an impact on the primary diffusion process changing its evolution as it makes the networked individuals more likely to adopt strategies targeted at self-protecting [124, 122, 120] and to slow diffusion . Since the multiplex networks constitute the most fit network structure to study these processes, their interdependence and co-evolution [155], it is crucial to do not separate the spreading process in the different layers, but [124, 122, 120] investigating and quantifying the impact of the co-evolution of the two processes in all the layers of the multiplex network (see Fig. 5.3). In addition, the multiplex networks, for its own nature, provide a tool to investigate the impact of heterogeneity on the spreading processes.
Traditionally, the awareness spreading is studied through the "Unaware-Aware-faded" (UAF) model where the possible transition states are: U indicating the unaware condition of nodes in the network; A is the state in which nodes start to raise their attention on epidemic spreading, understanding the risk associated to it; F is the state where nodes, aware of the epidemics, tend to decrease their attention on the topic, until it completely vanishes. When a node reaches this state, it maintains the same awareness, but it has no interest in increasing its awareness about the phenomenon [62]. The classical *UAF* reaction diffusion notation is:

$$U \xrightarrow{\lambda} A \xrightarrow{\delta} F \tag{5.14}$$

with λ and δ respectively awareness rate and fading rate. In order to capture the heterogeneity in both the spreading processes, it is useful to consider a dual heterogeneity in nodes' susceptibility and awareness in the different layers of the multiplex network, introducing a heterogeneous form of both the spreading models for epidemics and for awareness. For instance if we consider the *SEIR* model which is the most suitable model to represent the influenza-like illnesses we have a coevolving S^hEIR and a U^hAF expressed respectively through the following reaction-diffusion notations:

$$S^hEIR \Rightarrow S^h \xrightarrow{\beta_i^\alpha} E \xrightarrow{\gamma} I \xrightarrow{\mu} R \tag{5.15}$$

$$U^hAF \Rightarrow U \xrightarrow{\lambda_i} A \xrightarrow{\delta} F \tag{5.16}$$

This results in a variation of the infection rate β_α^i and the awareness rate λ_α^i where i stays for the single node and α indicates the layer $\alpha \in 1,...M$ of the multiplex network.
In order to explore the dynamics of the coevolution of social (or complex) contagion and awareness spreading on the multiplex network, it is useful to rescue on Dynamic Microscopic Markov Chain (MMCA). In accordance to which, initially it is assigned to each node a probability to be in one of the previous defined states. In particular, each node can be in the states: susceptible and unaware (SU), susceptible and aware (SA), infected and aware (IA), exposed and unaware (EU) (see Fig. 5.4). Some states are not reachable or do not exist, such as infected and unaware (IU) and recovered and unaware (RU), due to the assumption that if a node has been infected or recovered has experienced the disease, developing a measure of awareness. At time step t each node i can occupy one of the initial states, with probabilities $p_i^{SU}(t)$, $p_i^{SA}(t)$, $p_i^{IA}(t)$, and $p_i^{EU}(t)$ respectively. The probability of node i to not being infected at time step t is $q_i(t)$:

$$q_i(t) = (1-\overline{\beta}_i)\prod_j [1-a_{ji}p_j^I(t)\overline{\beta}_i] \tag{5.17}$$

and $r_i(t)$ is the probability of an unaware node i staying unaware at time step t, defined as follows:

$$r_i(t) = (1-\overline{\lambda}_i)\prod_j [1-a_{ji}p_j^A(t)\overline{\lambda}_j] \tag{5.18}$$

where a_{ij} are the elements of the adjacency matrix of each layer of the weighted multiplex network M_1 (for further details see. Section**??**). $\overline{\beta}_i$ and $\overline{\lambda}_i$ respectively are the mean values of the heterogeneous infection and awareness rate. The following MMCA equations represent the probability of each node of being in one of the states at time step $t+1$, as showed in Fig. 5.4:

$$\begin{aligned}
&p_i^{SA}(t+1) = q_i(t)p_i^{SA}(t) + (1-r_i(t))(1-\delta)p_i^{SU}(t);\\
&p_i^{SU}(t+1) = r_i(t)p_i^{SU}(t);\\
&p_i^{SF}(t+1) = \delta(1-r_i(t))p_i^{SU}(t);\\
&p_i^{IA}(t+1) = \gamma(1-q_i(t))(1-\mu)p_i^{SA}(t)+\\
&(1-\mu)p_i^{IA}(t));\\
&p_i^{EU}(t+1) = r_i(t)p_i^{EU}(t);\\
&p_i^{EA}(t+1) = (1-\delta)(1-r_i(t))p_i^{EU}(t)+\\
&(1-\gamma)(1-q_i(t))p_i^{SA}(t);\\
&p_i^{EF}(t+1) = \delta(1-r_i(t))p_i^{EU}(t);\\
&p_i^{RA}(t+1) = \mu(1-\delta)p_i^{IA}(t)+\\
&\gamma\mu(1-q_i(t))(1-\delta)p_i^{SA}(t);\\
&p_i^{RF}(t+1) = \mu\delta p_i^{IA}(t) + \delta\gamma\mu(1-q_i(t))p_i^{SA}(t);
\end{aligned} \tag{5.19}$$

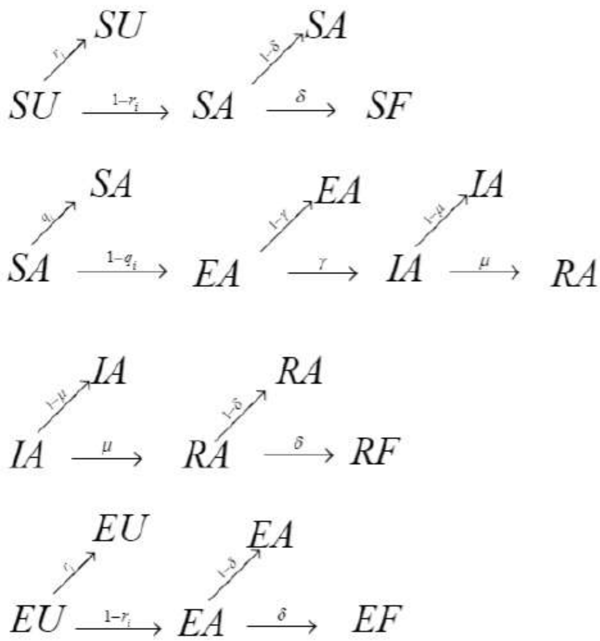

Fig. 5.4 Probability tree linked to the MMCA method, representing the states and the transitions of S^hEIR-U^hAF model, at each time step.

In order to obtain the contagion threshold, it is necessary investigating the steady state solution of the system constituted by the previous equations. When time $t \to +\infty$, there exists a contagion threshold β_C for the two co-evolving processes, so that the contagion can outbreak only if $\beta \geq \beta_C$. The contagion threshold is given by the order parameter ρ_i and it is defined as follows:

$$\rho^I = \frac{1}{N}\sum_{i=1}^{N} p_i^I = \frac{1}{N}\sum_{i=1}^{N} p_i^{IA} \tag{5.20}$$

Thus, starting from equation $p_i^{IA}(t+1)$ (see Eq. (5.19)), at steady state we have:

$$p_i^{IA} = \gamma(1-\mu)(1-q_i)p_i^{SA} \tag{5.21}$$

Since around the contagion threshold β_C, the informed probability is close to zero ($p_i^{IA} = \eta_i \ll 1$), the probabilities of being informed can be approximated as follows:

$$q_i = (1-\overline{\beta_i})[1-\overline{\beta_j}\sum_j a_{ij}\eta_j] = (1-\overline{\beta_i})(1-\omega_i) \tag{5.22}$$

where:

$$\omega_i = \overline{\beta_j}\sum_j a_{ij}\eta_j \tag{5.23}$$

Furthermore, close to the contagion onset the fading rate is approximately close to zero ($\delta \simeq 0$). Considering this approximation into Eq. 5.21 and omitting higher order items, Eq. 5.21 is reduced to the following form:

$$\mu \eta_i \simeq \gamma(1-\mu) p_i^{SA} \overline{\beta_i \beta_j} \sum_j a_{ij} \eta_j \tag{5.24}$$

The contagion threshold is obtained starting from the following condition:

$$\sum_j \left| \gamma(1-\mu)\overline{\beta_i} p_i^{SA} a_{ij} - \frac{\mu}{\overline{\beta_j}} t_{ji} \right| \eta_j = 0 \tag{5.25}$$

where t_{ji} are the elements of the Identity matrix. By defining the matrix H whose elements are given by: $h_{ij} = [\gamma(1-\mu)\overline{\beta_i} p_i^{SA}] a_{ij}$, the contagion threshold β_c is the value corresponding to the largest eigenvalue of the matrix H, which is given by $\Lambda_{\max}(H) = \gamma\mu/\overline{\beta_j}$, so finally we get: $\beta_c = \gamma\mu/\Lambda_{\max}(H)$. The onset of the epidemic is the minimum value β satisfying the Eq. 5.25. By denoting with $\Lambda_{\max}(H)$ the largest eigenvalue of H, we obtain the critical point of β_c which depends explicitly on the co-evolving dynamics. Even if we consider the critical value referred to the onset of the awareness spreading dynamics λ_c as a simple spreading process, when decoupled from the epidemic, the (β_c, λ_c) defines a sort of meta-critical point for the spreading dynamics.

5.2.1 Preventive Isolation and Overlapping Awareness

In order to provide a more realistic description of the diffusion phenomena, it could be useful to introduce additional compartments or allowing new transitions between the several compartments.

In [122] authors consider the two interdependent coevolving processes of epidemics and awareness in a multiplex network. In particular, the process of epidemic spreading is modelled as a S^hIR that is a variant of the classic SIR model mentioned above; with S^h a heterogeneous susceptible state which indicates the different susceptibility of each node in the multiplex network. The awareness diffusion among the nodes of the multiplex network is modelled as a $UAF(A^\pi)$ process 5.2 where A^π is an additional compartments which indicates the "overlapping awareness" related to a probability to have an additional awareness correlated to the first epidemic phenomenon. A^π is an alternative to the state F of the classical UAF in fact a node in the state A can decide to acquire a deepen knowledge on another aspect related to primary contagion process, obtaining an additional awareness, or to transit to the F state, fading its attention on the topic (see Fig. 5.5). Heterogeneity and overlapping

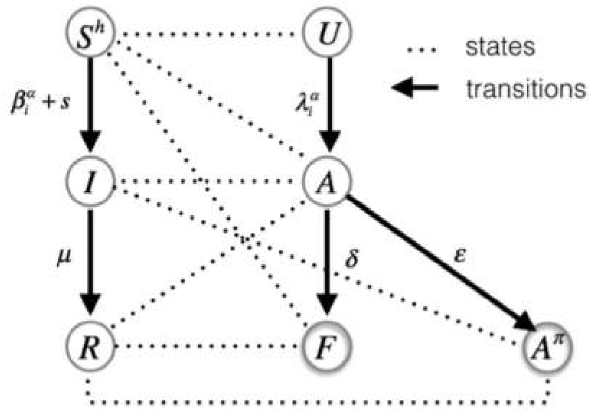

Fig. 5.5 Coevolution of social contagion and awareness spreading $S^hIR - UAF(A^\pi)$. States and transitions. Reprinted from [122].

awareness are crucial to describe a realistic spreading scenario and disentangle the complex coevolution of the two interdependent phenomena, without ignoring the influence of other aspects related to the contagion process. The two models are expressed through the following reaction-diffusion equations:

$$S^hIR \Rightarrow S^h \xrightarrow{\beta_i^\alpha} I \xrightarrow{\mu} R \tag{5.26}$$

$$UAF(A^\pi) = \begin{cases} U \xrightarrow{\lambda_i^\alpha} A \xrightarrow{\delta} F & if \varepsilon = 0 \\ U \xrightarrow{\lambda_i^\alpha} A \xrightarrow{\varepsilon} A^\pi & otherwise \end{cases} \tag{5.27}$$

where:

$$\lambda_i^\alpha = \gamma_i^\alpha \lambda \tag{5.28}$$

$$\beta_i^\alpha = \psi_i^\alpha \beta + s \tag{5.29}$$

with s representing the spontaneous contagion which evaluates the realistic condition to contract the contagion regardless the interactions with other nodes in the multiplex network. γ_i^α and ψ_i^α are heterogeneous factors which define the interdependence between the two spreading phenomena and the structural parameters.

At the first step, each node can be in the states; suscetible and unaware (SU), infected and aware (IA), susceptible and aware (SA) with the probabilities $p_i^{SU}(t)$, $p_i^{IA}(t)$, $p_i^{SA}(t)$ as defined in equations 5.17 and 5.18). Some states are considered not reachable or do not exist (i.e. infected unaware (IA), infected faded (IF), susceptible overlapping aware (SA^π) and faded overlapping aware (FA^π). In this case the MMCA equations are the following:

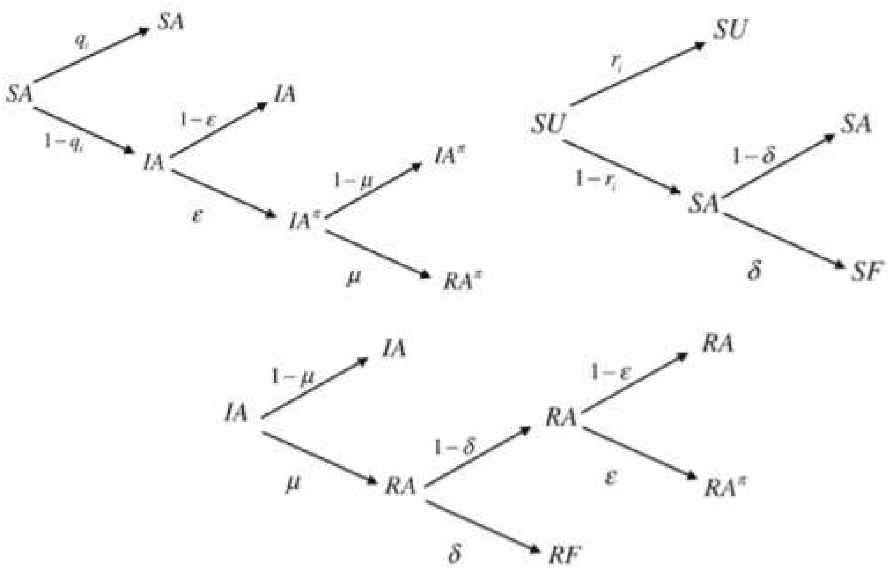

Fig. 5.6 Probability tree linked to the MMCA method, representing the states and the transitions of $S^hIR-UAF(A^\pi$ model, at each time step.

$$
\begin{aligned}
&p_i^{SA}(t+1) = q_i(t)p_i^{SA}(t) + (1-r_i(t))(1-\delta)p_i^{SU}(t);\\
&p_i^{IA}(t+1) = (1-q_i(t))(1-\varepsilon)p_i^{SA}(t) + (1-\mu)p_i^{IA}(t));\\
&p_i^{IA^\pi}(t+1) = \varepsilon(1-q_i(t))(1-\mu)p_i^{SA}(t) + (1-\mu)p_i^{SA}(t));\\
&p_i^{RA^\pi}(t+1) = \mu\varepsilon(1-q_i(t))p_i^{SA}(t) + \mu\varepsilon(1-\delta)p_i^{IA}(t);\\
&p_i^{SU}(t+1) = r_i(t)p_i^{SU}(t);\\
&p_i^{SF}(t+1) = \delta(1-r_i(t))p_i^{SU}(t);\\
&p_i^{RA}(t+1) = \mu(1-\delta)(1-\varepsilon)p_i^{IA}(t);\\
&p_i^{RF}(t+1) = \mu\delta p_i^{IA}(t);
\end{aligned}
\tag{5.30}
$$

For what concerns the contagion threshold, the equation 5.21 becomes:

$$p_i^{IA} = (1-\varepsilon)(1-q_i)p_i^{SA} \tag{5.31}$$

The equation 5.24:

$$\mu\eta_i \simeq (1-\varepsilon)p_i^{SA}\overline{\beta_i\beta_j}\sum_j a_{ij}\eta_j \tag{5.32}$$

The contagion threshold is obtained starting from:

$$\sum_j \left| \gamma(1-\varepsilon)\overline{\beta_i}p_i^{SA}a_{ij} - \frac{\mu}{\overline{\beta_j}}t_{ji} \right| \eta_j = 0 \tag{5.33}$$

In [124] the *SIR* model is enhanced in $S^h(i^p)IR$ introducing the state of preventive isolation i^p. The preventive isolation represents a strategy to delay or avoid the transition into the infected state, then choosing properly the isolation period, it allows reducing the infection rate or avoid the transition to infected if the network has already recovered. The selection of the nodes to be preventively isolated can depends on structural parameters, the awareness of the nodes or the socioeconomic factors. This epidemic model is diagramatically expressed by the reaction-diffusion notation, as follows:

$$S^h(i^p)IR = \begin{cases} S^h \xrightarrow{\hat{\beta}_i} I \xrightarrow{\mu} R \quad if w = 0 \\ S^h \xrightarrow{w} i^p \xrightarrow{\hat{\beta}_i^*} I \xrightarrow{\mu} R \quad otherwise \end{cases} \tag{5.34}$$

where $hat\beta_i$ is a heterogeneous susceptible rate which depends on structural parameters, depending on the multiplex network representation and socio-economic factors. The process of awareness spreading is modelled thanks to a heterogeneous UAF. As a result of the coevolution of the two dynamical processes, each individual in the multiplex network can only be in one of the three kinds of states: susceptible and unaware (SU), infected and aware (AI), and susceptible and aware (SA). In Fig.5.7, the MMCA method is illustrated the probability tree, which depicts at each time step, the possible states and their transition in our model.The state i^pU does not exist since, if a node has been isolated, it cannot be in the Unaware state (U) in fact, after being isolated preventively from the network, it knows that it could be a potential spreader of the disease. Similarly, the state *IU* (Infected Unaware) cannot exist, since an infected node will be surely aware of the epidemics. For the same reasons, the state *RU* (Recovered Unaware) does not exist as it has already recovered from an infection that it knows, then it will be surely aware of it. The probabilities to be in the initial states are indicated by 5.17 and 5.18 and integrated with the additional:

$$q_i^*(t) = (1-\hat{\beta}_i^*)\prod_j [1 - a_{ji} p_j^I(t) \hat{\beta}_i^*] \tag{5.35}$$

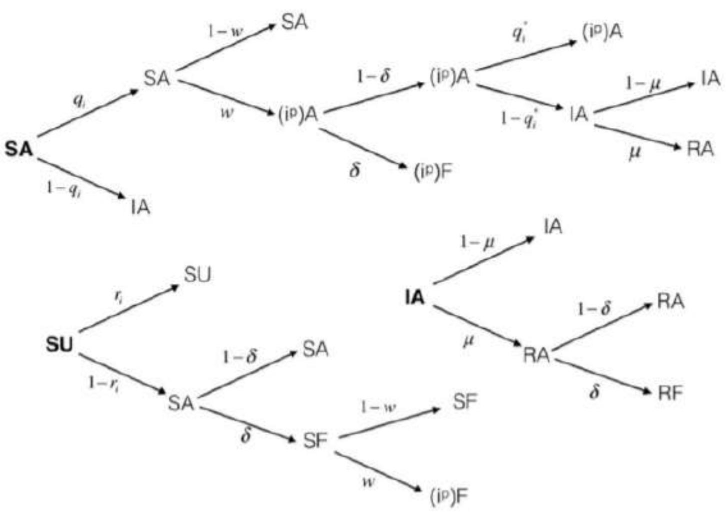

Fig. 5.7 Probability tree linked to the MMCA method, representing the states and the transitions of $S^h(i^p)IR-UAF$ model, at each time step.

The MMCA equation are the following:

$$
\begin{aligned}
&p_i^{SA}(t+1) = q_i(t)(1-w)p_i^{SA}(t) + (1-r_i(t))(1-\delta)p_i^{SU}(t);\\
&p_i^{SU}(t+1) = r_i(t)p_i^{SU}(t);\\
&p_i^{SF}(t+1) = \delta(1-r_i(t))(1-w)\delta p_i^{SU}(t);\\
&p_i^{IA}(t+1) = [(1-\mu)(1-q_i^*(t))(1-\delta)wq_i^(t) + (1-\mu)(1-q_i(t))]p_i^{SA}(t)) + (1-\mu)p_i^{IA}(t);\\
&p_i^{RA}(t+1) = [\mu(1-q_i^*(t))(1-\delta)wq_i^(t) + (1-\delta)\mu(1-q_i(t))]p_i^{SA}(t)) + (1-\delta)\mu p_i^{IA}(t);\\
&p_i^{RF}(t+1) = \mu\delta(1-q_i(t))p_i^{SA}(t) + \mu\delta p_i^{IA}(t);\\
&p_i^{(i^p)A}(t+1) = (1-\delta)wq_i(t)q_i^*(t)p_i^{SA}(t);\\
&p_i^{(i^p)F}(t+1) = \delta wq_i(t)p_i^{SA} + \delta w(1-r_i(t))pi^{SU}(t);
\end{aligned}
\tag{5.36}
$$

The contagion threshold is obtained following the same mathematical formulation of the previous cases.

Chapter 6

Complex approach for the Cognitive Profiling of edge nodes and Evaluation of the QoS in 6G scenarios.

Overview: The forthcoming 6G will attempt to rewrite the communication networks' perspective focusing on a radical revolution in the way entities and technologies are conceived, integrated and used. This leads to the need for innovative approaches with the aim at providing new directions to deal with future network challenges. The complex systems could become an enabling set of tools and methods to design a self-organized, resilient and cognitive network, suitable for many application fields, such as digital health or smart cities living scenarios. This chapter presents a 6G node's profiling technique based on the introduction of the multiplex dimension to detect a structural profiling and making also possible the analysis of the diffusion, the competition dynamics and the clustering techniques for the community detection in order to consider also a mesoscopic point of view. In addition to these aspects, considering that, the edge intelligence will enable the development of lightweight applications as microservices and requires edge intelligence also for guarantee adaptability in the service evaluation, in the second part of the chapter it is proposed a new evaluation model. This model, called CoKnowEMe (context knowledge evaluation model), follows a complex and dynamical approach and consists of three inter-operable levels and different networked attributes, to quantify the quality of microservices for Internet of Medical Things applications, depending on a changeable use's context. [1]

[1] The models, results and discussion presented in this chapter are shown and published in these contributions: [4, 121]

6.1 Introduction

The designing and modelling processes of 6G network need new paradigms to move the system from closed hierarchical structures towards open and distributed networks, including self-organization, self-adaptation and optimization of interactions and functions of nodes. Thus, it can be achieved through the introduction of complex systems approach as more widely explained in Section 2.2. The 6G technology has the ambition to provide new directions to deal with future network challenges. These ecosystems involve devices with constrained resources and computational capabilities and call for novel algorithms and a new characterization with the aim to dynamically manage lightweight and simple services, as a microservice, in mobile scenarios [53, 157]. It will address the constraints and the performance requirements of the applications and innovative services which need highly increasing resources, through innovative approaches [126].
The traditional attributes applied to measure and characterize communication networks such as interference, coverage, throughput, robustness and costs are not able to describe dynamics and crucial aspects of future wireless and mobile networks. That is why it is growing the interest in studying communication networks from a complex systems perspective, taking into account methodologies and tools built to analyse emerging behaviours, cooperative and collaborative dynamics among the elementary units of the system [126, 120, 125]. Since we are rapidly moving from closed to open and distributed system and to a completely dynamic topology that will be characterized by a vast heterogeneity, this requires an intelligence at node level. The node, in a fully user-centric network architecture, plays a key role in content diffusion, learning, computation and organization, and consequently a new characterization and profiling is becoming necessary. Together with these aspects, the innovative 6G services require also new innovative evaluating approaches, since they are treated, on the one hand, as resources for providing applications and, on the other hand, as a complex network of combined and virtualized elements. Based on these premises, in this thesis and in the following chapters, we start from the definition of cognitive system as: *"an autonomous system that can perceive its environment, learn from experience, anticipate the outcome of events, act to pursue goals, and adapt to changing circumstances"*[136].
In this chapter, it is firstly presented a profiling approach which embeds, step by step, the knowledge extracted from the introduction of the multiplex dimension, the analysis of the dynamics of collective phenomena as diffusion and competition, applying the epidemics spreading modelling and the EGT (see chapters 3, 4, 5 for further details), from the mesoscale hierarchical organization of the network in communities.
Then, it is proposed an evaluation scheme, called CoKnowEMe (context Knowledge evaluation model), modelled following a complex and dynamical approach targeted at the Internet

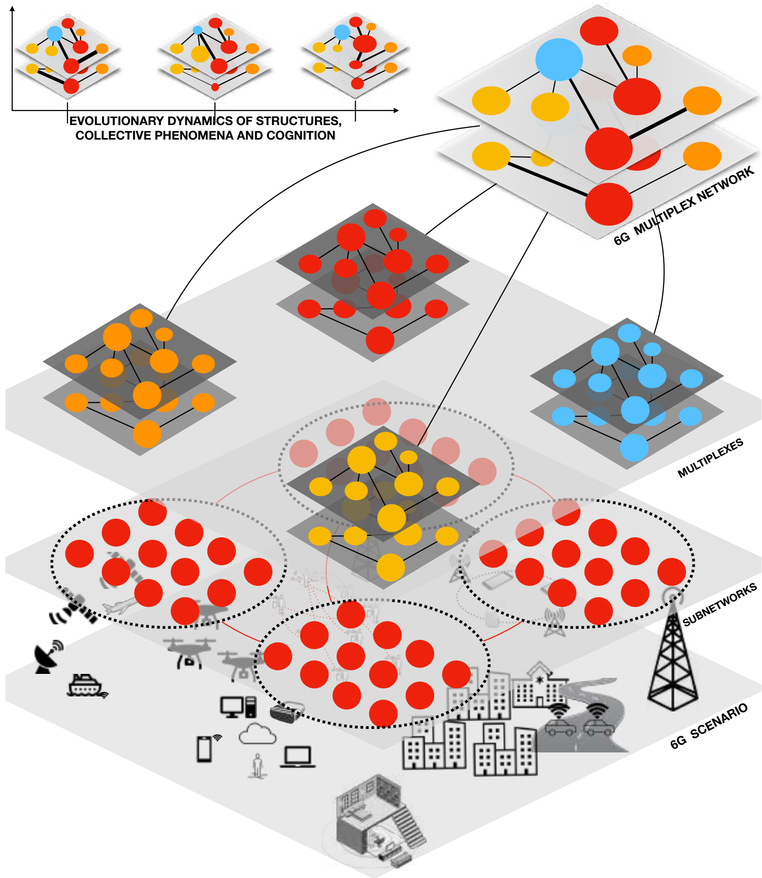

Fig. 6.1 Multiplex representation mined from 6G subsystems. Reprinted from [121].

of Medical Things (IoMT) in 6G. This scenario is particular challenging as the healthcare systems have to manage a wide variety of diseases, the increase of aging populations, the management of pandemics and jointly the effects of people awareness [120] and an increased number of treatments and patients [59]. In this context edge intelligence [111, 143, 68] will be a key enabling factor for future networks to improve performances, functions and services. In the edge application development the distributed and complex approach will be represented by the microservices able to develop modular lightweight application components. For both cases, the analytical model is presented and the results obtained with the simulations are discussed.

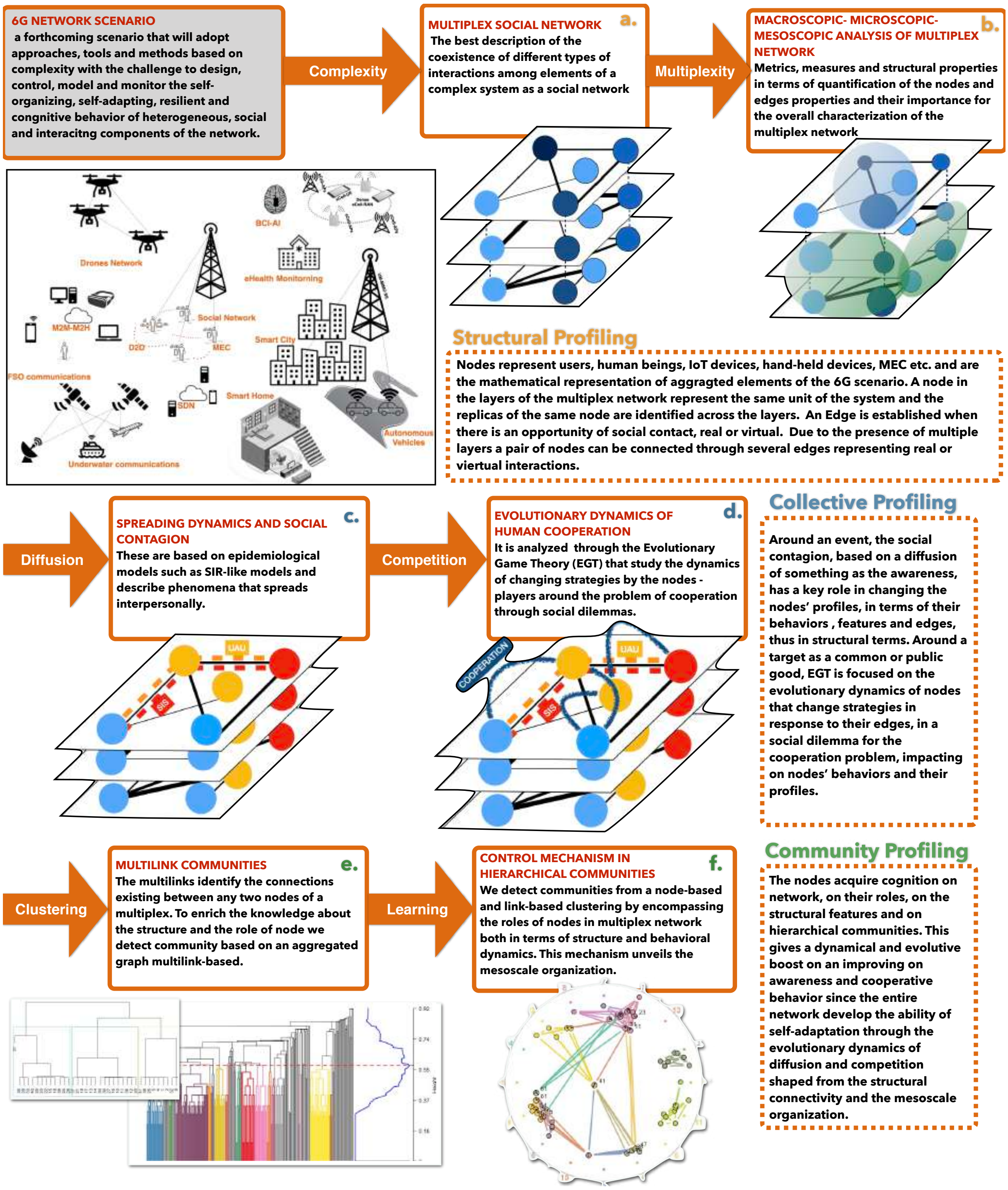

Fig. 6.2 Modelling Approach: a technical scheme of nodes' profiling in a 6G network scenario. Reprinted from: [121].

6.2 Cognitive Profiling of Nodes in 6G through Multiplex Social Network and Evolutionary Collective Dynamics

From the mobile users and their devices (from wearable to hand-held) or the heterogeneous smart devices that form the IoT networks to the plethora of entities of each sub-network that constitute a 6G environment, all these entities can be represented as nodes of a multiplex social network, as showed in Fig. 6.1.

The multiplex dimension (see sections 3.2 and 3.3 for definition and properties) offers a key change in perspective for the structural analysis, and it represents the suitable representation to study the emergence of complex properties of the network [24, 30]. Th 6G network is intrinsically suitable to be modelled as a multidimensional relational systems of different sub-networks, represented by various graphs that embed interacting elements in different way [126]. The designing, modelling and monitoring of the behaviour of these systems will be challenges to be addressed.

The modelling approach is depicted in Fig.6.2 and in the following sections the profiling technique is detailed through the introduction of metrics and parameters that enables the analysis of three different aspects, structural, collective dynamical and community-based.

6.2.1 Modelling Approach: Structural Profiling

Following the scheme presented in Fig.6.2, the multiplex social network $\mathscr{M}$ represents a 6G sub-network and it is referred to different kinds of interactions among nodes. A node represents an aggregation of different basic units of the network (as wearable or hand-held devices, IoT systems, etc). The multiplex network consists of a population of N nodes and $l = l_1, l_2..., l_M$ layers. Here $M = 2$ layers, where the layer l_1 is referred to a real contact network, extracted from a real case [89], while the second one is referred to a virtual layer following a theoretical scheme as, for example, a Scale-Free network [15] or a Small-World network [19]. In literature, the multiplex network is defined as showed in Chapter 3, where definitions in the case of weighted networks and definitions of structural measures such as degree k_i^l, edge overlap $o_{ij}^{[l_1,l_2]}$, the overlapping degree o_i and multiplex participation coefficient P_i are also shown. In the case of weighted multiplex networks, the latter are respectively expressed as weighted overlap o_{ij}^w and weighted overlapping degree o_i^w [96, 24]. The weights, that can be distributed heterogeneously, are strongly correlated with the structure [96], shedding light on the relevance of the links in a layer of the multiplex network representation. For that reason and with the aim at embodying social aspects into structural profiling, here, the weights links are defined as function of some key metrics, as follows:

$$w_{ij}^{l} = h_{ij}^{l}|aw_i - aw_j| \tag{6.1}$$

where h_{ij}^{l} indicates the tendency to interact with similar nodes (as equals devices) or with that ones that are in similar conditions (capacity, resources, etc.) [120, 24, 96]. Furthermore, it is included the gap value, between i and j, of the node awareness aw. In a fixed time T in which we observe the network and its activity, aw is defined as the awareness level of a node i, that represents acquired knowledge on the sub-network to which it belongs, that is about activity about task requests, as a result of a complex discovering process. For that reason, the awareness of a node i is estimated as function of the participation coefficient P_i, and the att_i attention level, as follows:

$$aw_i|_{t=T} = aw_i|_{t=0} + \sum_{T} att_{i|t-e} + P_i \tag{6.2}$$

The multiplex participation coefficient P_i ponder the awareness since it measures the heterogeneity of the number of neighbors across the layers of each node at the edge of the weighted link, measuring the probability of acquiring more knowledge as a result of different interactions distributed across the layers of the multiplex network [24, 120]. The P_i value is added to incorporate the richness of the knowledge extracted from the introduced multiplex dimension. Furthermore, the awareness can be computed as the result of the monitoring of the attention level, traced through the analysis of the user-generated data [69, 93, 120]. Data can be produced by devices in terms of willingness to cooperate for a set of tasks in IoT cognitive systems or it can represent the activity of nodes produced in social media during collective phenomena of interest, impacting on the widespread participation of networked users, on the behaviours of each node and its interactions and decisions in the dynamical evolution of the concerned phenomena [120]. The aforementioned multiplex network M is shown in the Fig. 6.3. A complete list of parameters and defined metrics with its fair meaning, referred to the structural profiling, is summarized in Table 6.1.

6.2.2 Modelling Approach: Collective Profiling

Multiplex networks representation, as showed in Fig. 6.3, constitutes the most suitable network structure to understand and investigate on collective dynamical processes and their complex interdependence [146]. In this second step, the attention is focused on the key features extracted from the analysis of parameters and statistical estimators of two interdependent and co-evolving spreading processes and the evolutionary dynamics of the cooperation among nodes.

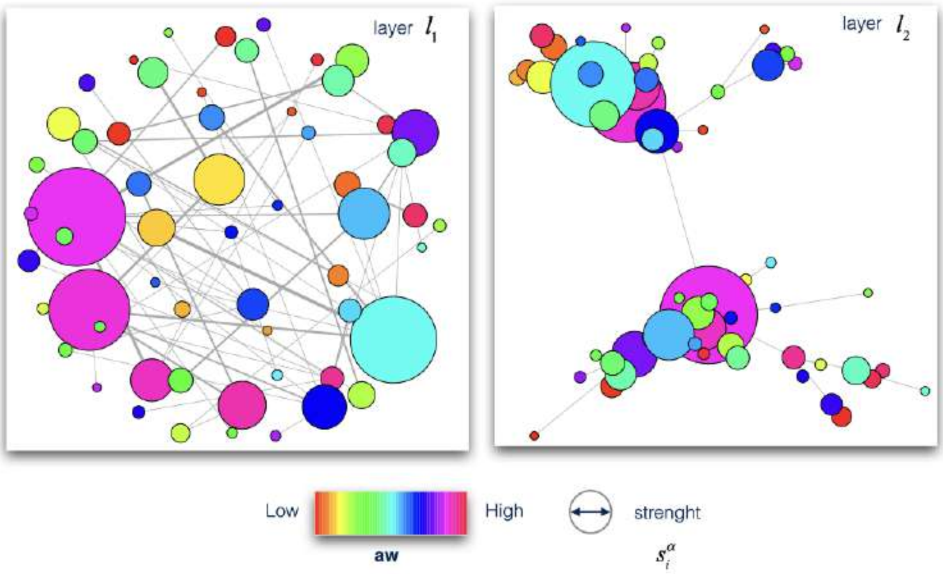

Fig. 6.3 Multiplex Network Representation. Reprinted from: [121].

Table 6.1 Structural Profiling Parameters and Defined Metrics.

Structural Profiling	Formalism	Description
Parameters [24, 96]	N	Population of Nodes of the Multiplex $\mathscr{M}$
	M	Numbers of Layers of the Multiplex $\mathscr{M}$
	A^l	Adjacency Matrix of the Layer l
	a_{ij}	Elements of the Matrix A^l
	k_i^l	Degree of Node i in the Layer l
	o_i	Overlapping Degree of Node i
	W^l	Weighted Adjacency Matrix of the layer l
	o_{ij}^w	Weighted Overlap of edge $i-j$
	o_i^w	Weighted Overlapping Degree of node i
	s_i^l	Strength of node i in the layer l
	Y_i^l	Inverse participation ratio of node i in the layer l
	P_i	Participation Coefficient of the node i
	H_i	Entropy of a node i
Defined Metrics	w_{ij}^l	Weights of interactions between $i-j$
	h_{ij}	Homophily of a pair of nodes $i-j$
	aw_i	Awareness of a node i
	$att_{i\|T-e}$	Attention of a node i during T around e

Firstly, it is studied the spreading of two interdependent processes in the multiplex network M, modeled as disease spreading process [122] and thought as "composed-SIR" models, that is as an extension of the classical SIR epidemic model [137]. One process is referred to a specific phenomenon as epidemic [120], collective attention [69] or a social contagion [42], while the second one is related to the diffusion of the awareness on what is transmitted through the first one [63, 122]. Heterogeneity and awareness, for each node, are included in order to describe the impact of the diffusion and competition into the structural connectivity and the evolutionary dynamics. Each node has a different awareness *aw*, representing the acquired knowledge from an interest or participation on a collective phenomena. As a consequence, each node, will be heterogeneously prone to join a diffusion process, since the awareness acquired has an influence on the behaviours of nodes. For what concern the two co-evolving spreading processes considered, the first one is based on the content shared or a phenomena of interest. Taking into consideration the nature of the phenomena or content, and it is expressed in terms of reaction-diffusion equations, following two different hypothesis as indicated below as the S^hIS^h or S^hIR spreading processes:

$$S^hIS \Rightarrow S^h \xrightarrow{\beta_i^\alpha} I \xrightarrow{\mu} S^h \tag{6.3}$$

$$S^hIR \Rightarrow S^h \xrightarrow{\beta_i^\alpha} I \xrightarrow{\mu} R \tag{6.4}$$

The S^hIS^h can occurs when a node, based on its interactions, becomes prone to participate to the diffusion, and after that it returns in the condition to the starting pools of nodes. Differently, in the S^hIR the last transition is replaced by the step which occurs when a node have acquired a permanent condition and it is not available to participate again to the diffusion. Both models are characterize by the states S^h defined as "heterogeneous susceptible state", where a node is predisposed to be involved in the spreading process [122]. The state I indicates the condition in which a node is involved or infected, while R represents the recovered state. As shown in Chapter 5 the probability of call off the diffusion is equals to μ, while the β_i^α is the diffusion rate for each node i at each layer α in the multiplex network M. The latter represents the probability that a node i in the layer α is predisposed or susceptible to be involved in the diffusion process. Here, it is assumed that, the involvement for a node in the network means that a node i is in the state of informed or infected. The heterogeneous diffusion rate depends on the weighted structural connectivity through the measures of inverse participation ratio Y_i^α [96] and the rate of awareness λ_i^α, defined in Eq. 6.8.

$$\beta_i^\alpha = \frac{1}{1+\lambda_i^\alpha} \cdot \frac{1}{Y_i^\alpha} \tag{6.5}$$

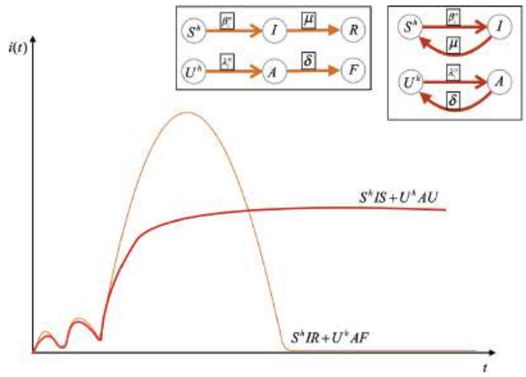

Fig. 6.4 Density of Involved Nodes $i(t)$ versus time t, on the two processes in co-evolution. Reprinted from: [121].

Similarly, the second spreading process, focused on awareness diffusion, is diagrammatically expressed in terms of reaction-diffusion equation also in two possible different cases, as follows:

$$U^hAU^h \Rightarrow U \xrightarrow{\lambda_i} A \xrightarrow{\delta} U^h \tag{6.6}$$

$$U^hAF \Rightarrow U \xrightarrow{\lambda_i} A \xrightarrow{\delta} F \tag{6.7}$$

with λ_i^α and δ, defined as transition rates. There is a difference between the rate of awareness λ_i^α for each node i at each layer α of the multiplex M and the rate of awareness after being aware. The U^h state, expresses a condition in which a node is heterogeneously unaware while in A it is aware about the phenomena that spreads interpersonally in the network. In the second case the state F is introduced as the "faded state", in which a node decreases the attention and the interest to improve its knowledge about the phenomena of interest. The rate of awareness is expressed as follows:

$$\lambda_i^\alpha = \frac{s_i^\alpha}{1+s_i^\alpha} \cdot \lambda \tag{6.8}$$

with s_i^α the strength of node i in the layer α of the multiplex network M [96].

Starting from the assignment of a state probability for each node i in M, to be in one of the initial states as (SU)-(SA)-(IA), and choosing the suitable spreading models for the co-evolution process, as indicated in Fig. 6.4 and expressed in Eq. 6.3 and 6.4, it is added, in the profiling process, some features extracted from the analysis of the co-evolution in the multiplex network considered. To obtain the contagion threshold it is applied the MMCA method, investigating the steady state of the system, indicated as β_c. Following the mathematical approach, as expressed in [120], the density of involved nodes ρ_i:

$$\rho^I = \frac{1}{N}\sum_{i=1}^{N} p_i^{IA} \tag{6.9}$$

where p_i^{IA} are the probabilities of being involved and aware. On this matter, it is important to underline that, the threshold model depends on the complex dynamical interplay between social contagion and the awareness spreading in M and the values of β_i^α that change in accordance with the awareness state λ_i^α, the network structure of M, and the double heterogeneity expressed in S state and U state. Consequently, the *aw* awareness of a node as expressed in Eq. 6.2 depends also on the β and λ value in terms of attention which represents the social-aware factor that varies in function of the two rates. Both processes co-evolve modelling the sharing or participation in terms of content, interests, attention and awareness and in terms of active or passive involvement [42, 63, 125]. Furthermore, for what concerns the cooperative behaviours and its dynamics among nodes, which include social factors in their aggregated nature, by introducing the game theoretical approach [48]. In the analysis of the interdependent collective dynamics the four social dilemmas (described in Chapter 4) are run and compared for a number of rounds such that a dynamical steady state is reached, in order to describe not only the problem of cooperation but also its evolution. Nodes are treated as players that, in each elementary round of the game can decide to change or maintain its strategy, playing the game with all its neighbors in both layers of the multiplex M, in line with the Fermi function $W(S_x \rightarrow S_y)$, expressed as follows:

$$W(S_i \rightarrow S_j) = c_i \eta_i \frac{1}{1 + exp[\frac{P_i - P_j}{\delta_{ij} K}]} \tag{6.10}$$

Firstly, with this function the payoff difference $P_i - P_j$, the homophily measure δ_{xy}, a communicability measure η_x and a noise factor K to evaluate the probability that a player i on the layer l_1 decides to adopts the strategy S_j of node j playing on the layer l_2 are considered [48]. Accounting for that, at time step t, each node can occupy one state of the co-evolving spreading processes, and considering that, $q_i(t)$ represent the probability of node i not being involved and with $r_i(t)$ the probability of unaware node i staying unaware at the same time step t, we include in the Fermi function the dependency from the c_i factor, as defined as follows:

$$c_i = \frac{1 - q_i}{1 - r_i} \tag{6.11}$$

This includes the joint impact of the co-evolving spreading processes and the evolutionary dynamics of the cooperation among nodes in the multiplex network M, assessed in the

Table 6.2 Collective Profiling Parameters and Defined Metrics.

Collective Profiling	Formalism	Description
Parameters[120]	S^h	Heterogeneous Susceptible State
	I	Involved State
	R	Recovered State
	U^h	Heterogeneous Unaware State
	A	Aware State
	F	Faded State
	μ	Probability to transit from state I to state R
	δ	Fading Rate
	ρ_I	Density of Infected Node
Defined Metrics	β_i^α	Heterogeneous involvement rate
	λ_i^α	Heterogeneous awareness rate
	$W(S_i \to S_j)$	Fermi function
	c_i	Impact factor of the co-evolving processes

temporal window T. Parameters and defined metrics of the collective dynamics aspects are summarized in the Table 6.2.

6.2.3 Modelling Approach: Community Profiling

The whole multiplex network M can be also described via its multilink [99] with the aim at describing a mesoscopic dimension. Every pair of nodes in $\mathscr{M}$ is connected by a multilink $\vec{m}_{ij} = (m_{ij}^{[l_1]}, m_{ij}^{[l_2]})$ with l_1 and l_2, layers of the multiplex $\mathscr{M}$, with $m_{ij}^l = a_{ij}^l$ indicating the set of all links connecting these nodes in the different layers [99]. If $\vec{m} = 0$ there are no interactions between the two nodes in the multiplex $\mathscr{M}$. This measure shows the basic motif [24] that contribute to the unveiling of correlations between structure and function of a network [21]. It is considered a weighted aggregated network $\widehat{G}^w$, based on the multilink $\vec{m}_{ij}$, with the adjacency matrix $A_{ij} = \theta(\sum a_{ij}^{[l]})$, with $\theta(x)$ a step function [99]. For detecting community it is introduced the multidegree $k_i^{\vec{m}}$ for each node i of the population, showing how many multilinks $\vec{m}$ are incident on the node i [96]. In line with the previous steps of profiling, Two community detection methods are proposed, introducing the mesoscopic analysis of the network. The resulting hierarchy embeds both the richness of the structure and the collective dynamics in the cognitive profiling since each node belongs to a community with a specific role that dynamically tunes in response to the changes in behaviours, and social factors. Thus, the different interdependent steps of profiling are combined and two hierarchical clustering technique are applied to the multiplex network $\mathscr{M}$, respectively a

Table 6.3 Community Profiling Parameters and Defined Metrics.

Community Profiling	Formalism	Description
Parameters [96, 24]	$\overrightarrow{m}_{ij}$	Multilink between i, j
	$\widehat{G}^w$	Weighted Aggregated Network
	A_{ij}	Elements of $\widehat{G}^w$
	$k_i^{\overrightarrow{m}}$	Multidegree of node i
	n_{ci}	Number of cooperations
	c_b	Betweenness Centrality
Defined Metrics	$hc_{ij\|\widehat{G}}$	Score Function for dissimilarity structure

node-based and a link-based technique. The node-based hierarchical clustering analyses a set of dissimilarities through the application of an agglomeration method.The dissimilarity structure is based on the distance between each pair of nodes in function of the number of cooperations n_{ci}, the social dilemma, the betweenness centrality c_b, and the multidegree $k_i^{\overrightarrow{m}}$ [24, 99]. The dendogram is constructed via the hierarchical clustering method containing information about the structure and based on the dissimilarity matrix. More specifically, it is evaluated for each pair of nodes a defined score function to estimate the distance between them, as indicated below:

$$hc_{ij|\widehat{G}} = \frac{c_b(i)}{n_{c_i} + k_i^{\overrightarrow{m}}} - \frac{c_b(j)}{n_{c_j} + k_j^{\overrightarrow{m}}}. \tag{6.12}$$

With this approach, each node belongs to a community with a role in the hierarchical organization of the multiplex network $\mathscr{M}$. Similarly, by constructing the aggregated graph multilink-based $\widehat{G}$, it is furthermore applied a hierarchical clustering by grouping instead the links in different communities showing a hidden mesoscale structural organization, highlighting how nodes can belong, at the same time, to different link-based communities.

6.2.4 Performance Evaluation

Simulation Setup

Simulations have been performed considering a weighted multiplex network $\mathscr{M}$ as explained in section 6.2.1. The model, the computation and the results have been made using the programming language R and the IDE RStudio. The figures were generated thanks to the package Plotly and Linkcomm [116], [133], [128][80]. It is considered a population $N = 61$ in the two layers l_1, l_2 representing two distinct kind of weighted interactions and connectivity

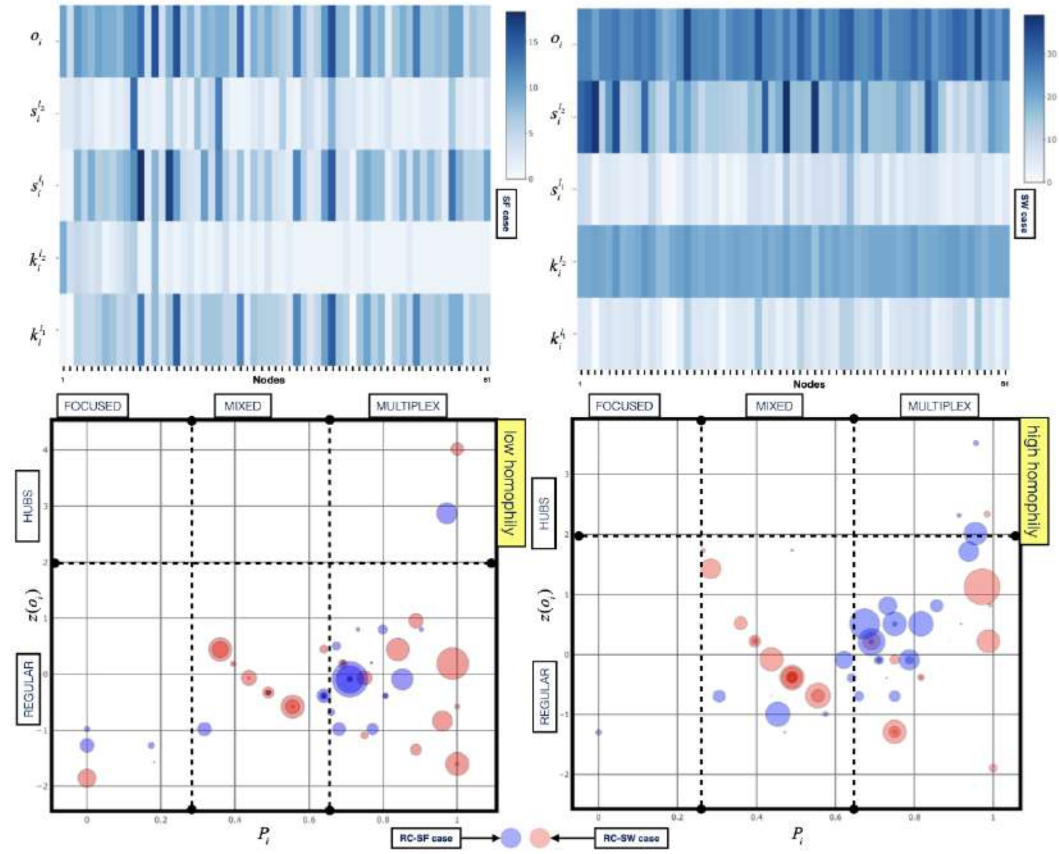

Fig. 6.5 Roles of Nodes from Structural Analysis. Reprinted from [121].

between nodes. In the first layer l_1 the interactions are based on the graph extracted from a real contact network [89], while in l_2 it is considered a theoretical scheme for the same population of nodes N.

Numerical Results

In the Fig. 6.5 it is displayed how the structural heterogeneity in the multiplex representation of the networks leads to highlight several key aspects for the structural roles of nodes. For a heterogeneous weighted multiplex network the metrics computed are the degree k_i^l, the strength s_i^l and the overlapping degree o_i as indicated in the two heath-map plots. Both plots display metrics for the multiplex $\mathscr{M}$ composed by the first layer based on real contact network while through the second layer the case of a scale-free network (in the top-left plot) with a small-world network (in top-right plot). For the sake of clarity, the first resulting multiplex $\mathscr{M}$ are indicated as $RC-SF$, and the second one as $RC-SW$. As showed in Fig. 6.5, the findings exhibit two different levels of heterogeneity. Is is evident how in the $RC-SW$ case there is a small heterogeneity due to a high clustering and modularity, meaning

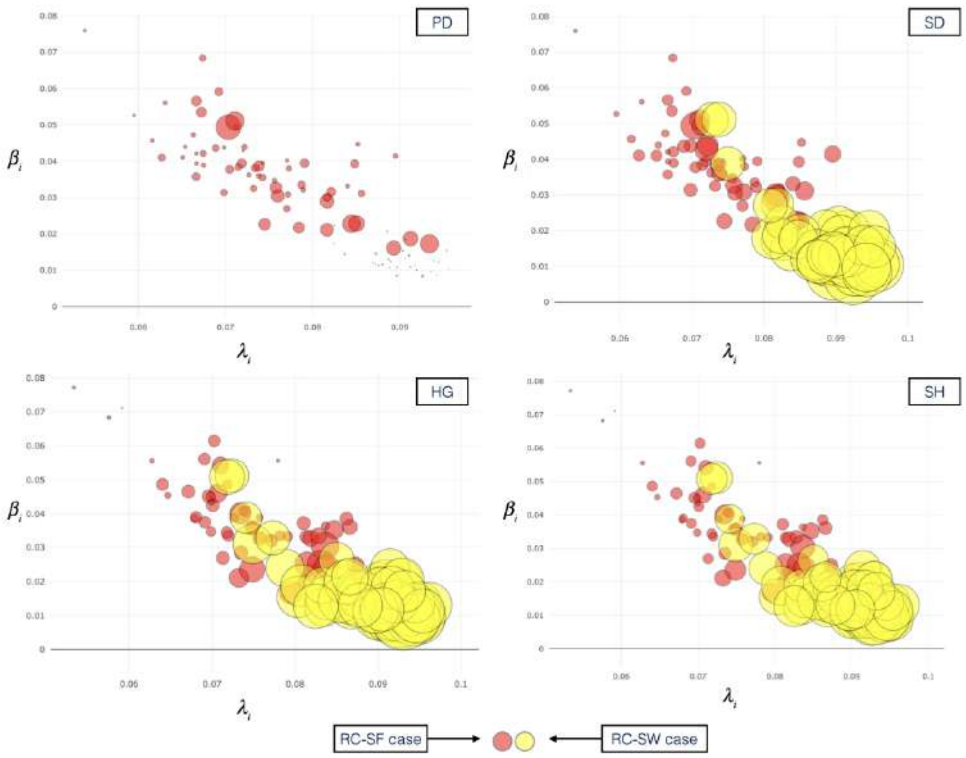

Fig. 6.6 Roles of Nodes from Collective Dynamics Analysis. Reprinted from: [121].

that there are groups of nodes more highly connected than the rest of the network with an abundance of high degree nodes, that act as hubs of the network. Instead, in the $RC-SF$ case, there are few hubs in the network since it exhibits a highly heterogeneous and high degree correlations. In the other two panels below of the Fig. 6.5 the curves correspond to the distribution of the participation coefficient P_i, in the range $[0,1]$, considering this variation in function of the Z-score of the overlapping degree, $z(o_i)$. Profiling features are extracted structurally classifying the nodes of the multiplex in three classes, focused, mixed and multiplex nodes, putting in evidence the fitness based on the two cases $RC-SF$ and $RC-SW$, the awareness distribution of aw_i and the homophily distribution of the values h_{ij}, in accordance with the modelling approach. These findings highlight an increasing of the P_i value in both cases ($RC-SF$ - $RC-SW$), and a higher density of regular multiplex nodes. Decreasing the homophily (from the left plot to the right plot below) the findings exhibit a decreasing of P_i for $RC-SW$ case that has a more homogeneous distribution with a higher density of regular mixed nodes. Differently, in the same condition, in the $RC-SF$ the findings show an increasing of $z(o_i)$ and a higher density in the multiplex hubs, since although there is a higher value of homophily the structural heterogeneity of the topology produces a more heterogeneous distribution of nodes' roles. The Fig. 6.6 points out the profiling features embedding a measure of how a node of the multiplex structure is involved in the collective dynamics. The findings related to diffusion and competition dynamics are shown, by displaying the trend of infection rate β_i in function of the awareness rate λ_i. The plots show the resulting trend, in the plane $\lambda-\beta$, of the spreading dynamics in conjunction with the cooperative behaviour of nodes in the multiplex M, taking into consideration the two cases $RC-SF$ and $RC-SW$, and the four social dilemmas PD-SD-HG-SH. Since the diffusion dynamics impact on the evolutionary dynamics of cooperation it is compared the modelling of the conflict situations with the different dilemmas. Results highlight how the increasing of the awareness rate λ_i, and the consequently decreasing of infections rate β_i produce an impact on the collective cooperation dynamics. Namely, in case of social dilemmas in which the cooperation dominates the defection as SD, HG and SH, a more homogeneous number of cooperation for each node is more evident in the case of $RC-SW$. Differently, in the plot referred to the PD game, in case of $RC-SF$ there is a more heterogeneous distribution of cooperative behaviour. In addition, in the PD, the increasing of λ_i results in a decreasing of β_i, in both cases $RC-SF$ and $RC-SW$, while in the other social dilemmas cases this impact is stronger in $RC-SW$ then in $RC-SF$. What is more, in $RC-SF$ case and SD-HG-SH, the decreasing of β_i with the increasing of λ_i is up to a specific threshold, resulting in a change in strategy, in accordance with the Fermi function as expressed in Eq. 6.10, shedding light on

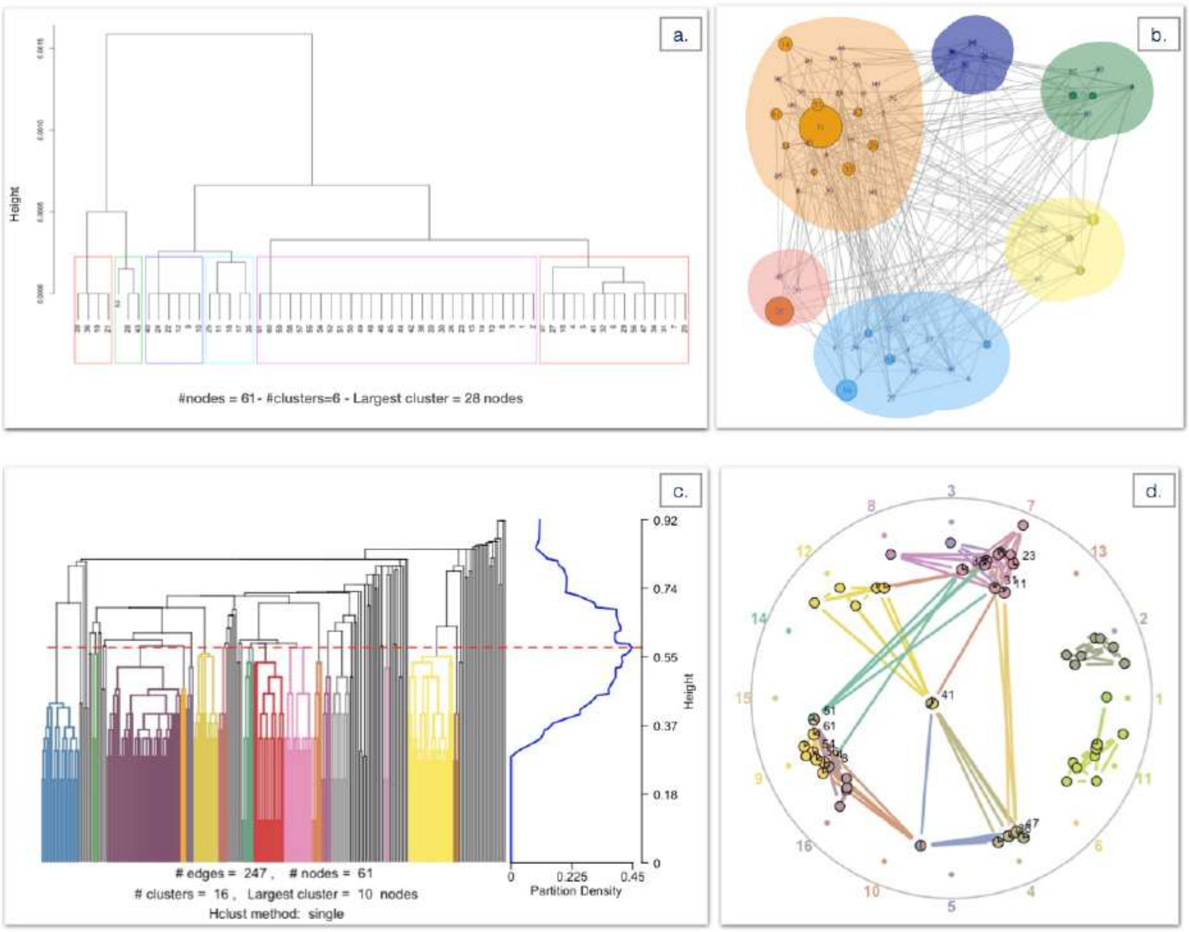

Fig. 6.7 Roles of Nodes from Community Analysis. Reprinted from: [121].

the increased size of nodes in line with the increasing average in number of cooperation for each node.

In Fig. 6.7 there are four panels linked to the community profiling. By defining the dissimilarity between nodes based on Eq. 6.12 it is considered a hierarchical clustering of nodes as showed in the (a),(b) plots of the Fig. 6.7, that respectively exhibits the dendrogram and the graph based coloured partitions of the six different communities. The detected groups of nodes based on a complex score function that take into consideration the structural and collective dynamical properties, show a community connectivity lower than the multiplex one. This unveils how the multiple interactions in the multiplex structure of each node represent a key point in a hierarchical characterization of the nodes' roles. In the plot (c) and (d) (produced through the R package "linkcomm" [80]) of the Fig. 6.7, results linked to the multilink and the link-based hierarchical clustering to reveal the richness of the network at the mesoscale level are showed. The panel (c) displays the cluster dendrogram and the sixteen communities detected, and (d) a graph visualization of the multilink-based aggregated graph $\widehat{G}$. This methodology sheds light on in what measure the nodes of the multiplex structure, independently on its layer activity, can belongs to different community revealing the hidden information extracted from the mesoscale structure organized in communities. The findings demonstrate that since the nodes belongs to multilinks communities, on average they have a high community activity suggesting that the network can be expanded in many layers of different interactions. Moreover, the plot (d) of Fig. 6.7 underlines also the brokering function of certain nodes among whose belonging to many communities (dots with multiple colours), playing a pivotal role in the cognitive collective dynamics.

6.3 CoKnowEme: An Edge Evaluation Scheme for QoS of IoMT Microservices in 6G Scenario

A very challenging scenario is represented by IoMT as it has the capability to interconnect various heterogeneous entities ranging from personal devices and healthcare providers to private companies. The advent of IoMT in a heterogeneous and dynamic environment is mainly due to increase in use and development of connected and distributed medical devices, leading to potential application and services that need to address several concerns. Since a cloud of Things and IoMT produce a huge amount of data concerning consumers, it is possible to combine services/data from one or multiple Things with services/data from virtual resources to dynamically allocate the connected heterogeneous things that can share resources, archives and tasks to provide services [65]. It is essential to understand what is the quality of this kind of dynamical services which is characterized by an increasing demand for stringent requirements as data-driven and defined by extremely low-latency, ultra-reliable, fast and seamless wireless and mobile connectivity, including also the shift of distributed communications, control, computing, sensing and energy, from its core to its end nodes (edge clouds, Mobile Edge Computing (MEC), etc.).
The evaluation approach presented in this chapter is schematically displayed in Figure 6.8, where it is shown a 6G scenario with heterogeneous sub-networks and systems and the plethora of entities from the mobile users and their devices (from wearable to hand-held) or the heterogeneous smart devices that form the IoT and IoMT networks. The aim of this representation is to schematically introduce a complex approach for both IoMT services and for the evaluation scheme, since each module can represent a resource in terms of data or computed output, in a multilevel architecture, which exploits the opportunity introduced by

the edge intelligence.
The evaluation model proposed is presented as a dynamic model capable of conveying the knowledge acquired from each of the levels considered and from their combination. Moreover, for each level, several attributes and sub-attributes have been identified as the key aspects to be investigated with the aim of mining the knowledge referred to the different features considered. The quantification of the outputs uses the Weighted Sum Model (WSM) [152], in which the weight of the values of the corresponding attributes is determined by the context of use, which plays a key role within the model as it manages how to modulate the intensity of the attributes of each concept, increasing the effectiveness and accuracy of the evaluation and its adaptability to the interconnection of the different elements of the IoMT services.
The dynamical schematic evaluation model jointly with an analytical model for each level considered is provided in the next paragraphs.

6.3.1 Architectural and Analytical Model

The evaluation model proposed in this chapter is aimed at assessing, on edge level of a 6G scenario, the microservices of IoMT systems. As microservices are dynamically created at the edge level, similarly the evaluation follows the same approach. The edge nodes deal with the computing, storage, integration of heterogeneous data, the dynamical structural organization in space and time, according to a multiplex and complex approach [11], and the evaluation. The evaluation scheme, presented in Figure 6.8, is designed following the key aspects of a lightweight application and in a modular way with interdependent and chained levels. Each output, from one of the level or from a combination of more than one, can be seen as a resource for the edge nodes that are organized to dynamically and consciously use and reuse the available resources and also to create new ones.
This approach adds a key point in the design of the edge intelligence since in addition to carrying out services respecting the users' requirements, making the best use of resources, it enables edge entities to assess the impact of the application on end user in a collective and dynamic way, close to the user itself. In the Figure 6.9, starting from the complex approach it is detailed the research method. Both the microservice construction and the evaluation scheme applied to it follow the complex approach. In fact, here, the microservice construction is considered as the result of a networked structure of resources that can change dynamically and shape a complex graph that follows the properties of the structures that arise in a wide array of different contexts such as technological and transportation infrastructure, social phenomena and biological systems [110, 18].
The considered CoKnowEme architectural model is based on a three-level structure: Ac-

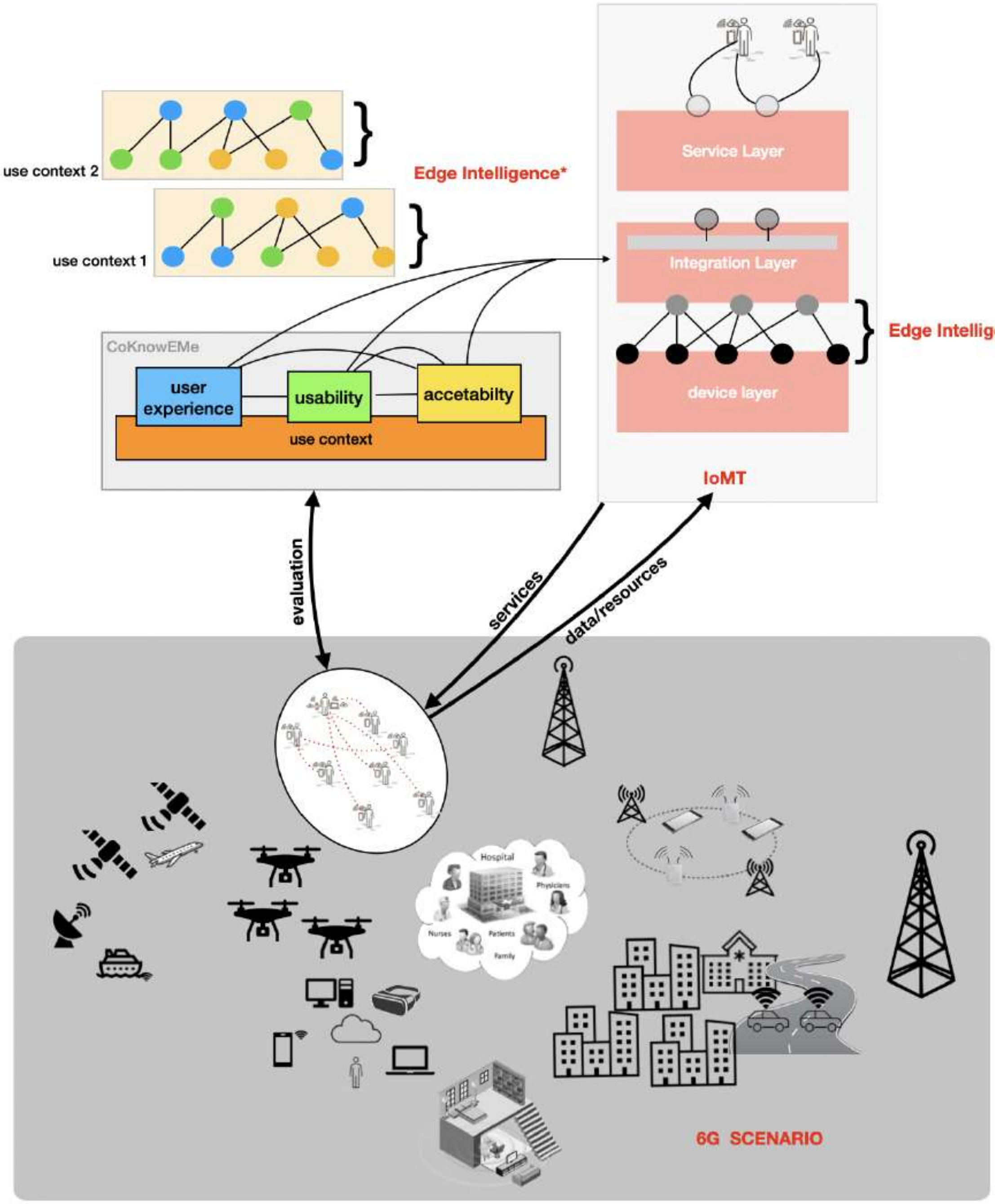

Fig. 6.8 Evaluation in a 6G scenario for IoMT microservices. Reprinted from: [4]
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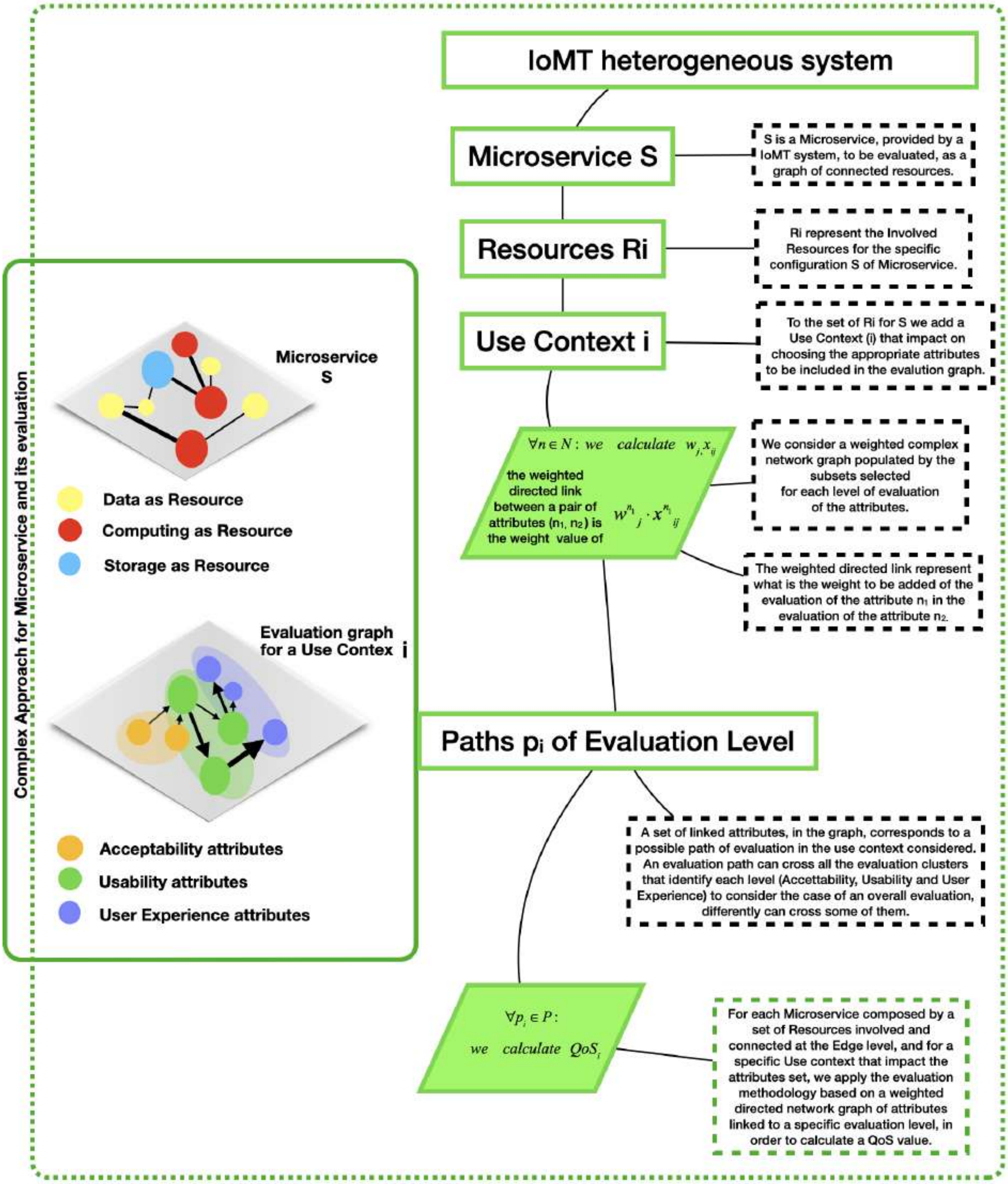


Fig. 6.9 Complex Approaches for Microservices and their Evaluation. Reprinted from: [4].

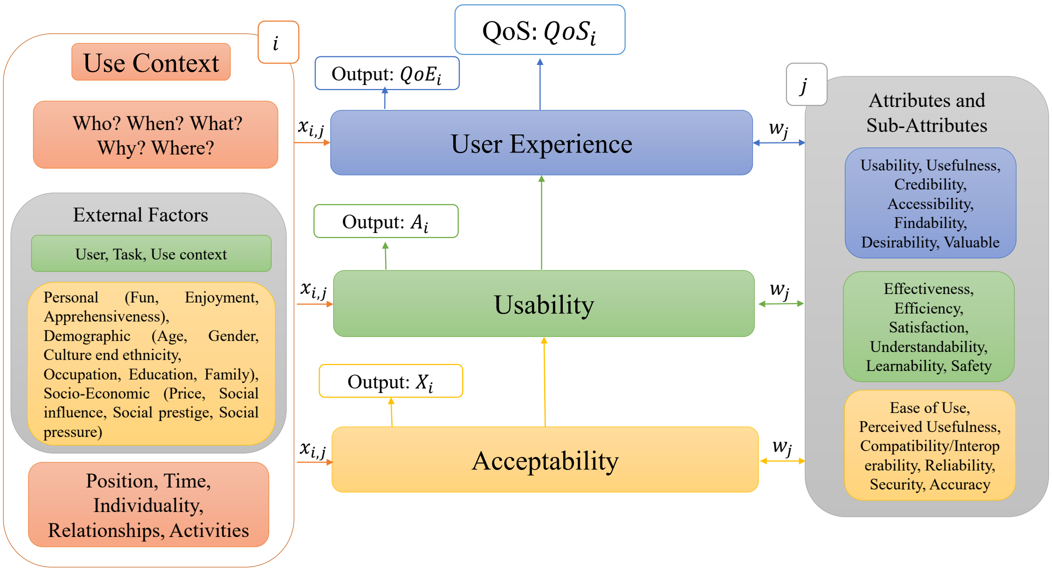


Fig. 6.10 CoKnowEMe, architectural model. Reprinted from: [4].

ceptability, Usability and User Experience; each of them embraces a different aspect of the service, always taking into consideration the context of use, as shown in Figure 6.10. The adaptability of the model is given not only by the desired choice of versatile concepts that are able to adapt to different fields, but also by the ability of the model itself to allow the separate evaluation of concepts. Each level has been designed both to be used individually, since each level corresponds to a precise concept that can be fully evaluated thanks to its set of attributes and for the construction of a multi-conceptual evaluation. Each layer acts as a base for the next level resulting in a set of building blocks of the entire evaluation.

The proposed model is based on the WSM [152], which is widely used for multi-criteria analysis and allows, thanks to a composition of weights and parameters, to consider the importance of each parameter in a different way. In the proposed CoKnowEMe the parameters are the values resulting from the evaluation of individual attributes, while the weights are determined, from time to time, in accordance with the considered use context. In this way, the context of use determines the relevance of each attribute through the weights.

Let us assume that $x_{(i,j)}$ is the weight of an attribute j in context i and that w_j is the value of attribute j, calculated using the corresponding metrics, where $i = [cx]_1, [cx]_2, \ldots, [cx]_m$, which are all the possible m contexts and $j = j_1, j_2, \ldots, j_n$, which is all the n attributes related to the considered concept. Therefore, X_i denotes the value of the evaluation of the concept under consideration (acceptability, usability and user experience) in a context i and it is the weighted average of all the attributes related to the considered concept; X_i is calculated as

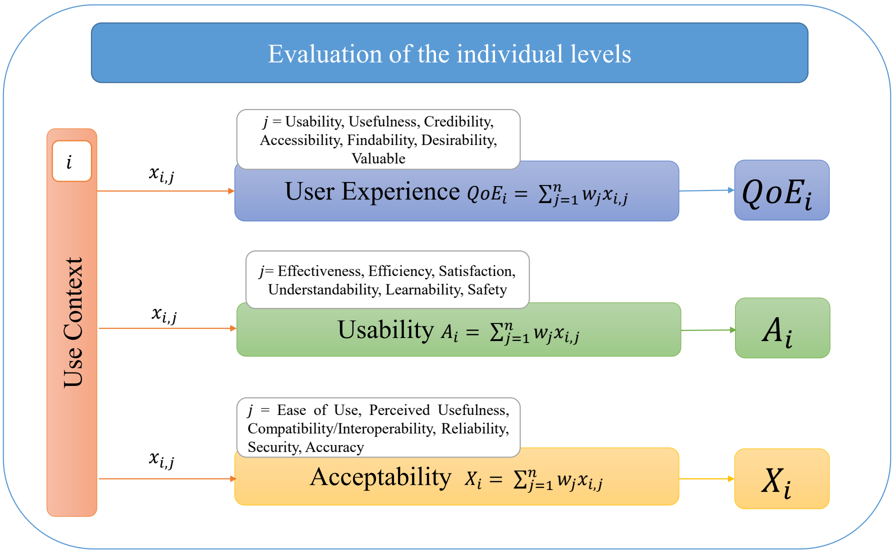


Fig. 6.11 Evaluation of the individual levels. Reprinted from: [4].

follows:

$$X_i = \sum_{j=1}^{n} w_j x_{i,j} \tag{6.13}$$

Equation 6.13 is applied at each level of the proposed architectural model and the obtained results indicate the degree of acceptability, usability or user experience of a service to be assessed in a given context of use. It should be noted that Equation 6.13 can be directly applied to evaluate a single level (see Fig. 6.11), while, for an overall assessment which takes into account all the levels, it is necessary to consider the results obtained at the previous levels as an attribute of the next ones (see Fig.6.12). In more detail, in order to conduct a complete assessment of the entire service, the steps to follow are:

1. considering the level of acceptability, the first, starting from the bottom, X_i calculated as expressed in Equation 6.13; this value will constitute the output of the considered level and quantifies the acceptability degree of the service;

2. going up to the usability level, we have to consider what has been obtained at the level of acceptability, as expressed in Equation 6.14:

$$A_i = \sum_{j=1}^{n} w_j x_{i,j} + X_i x_{i,X_i} \tag{6.14}$$

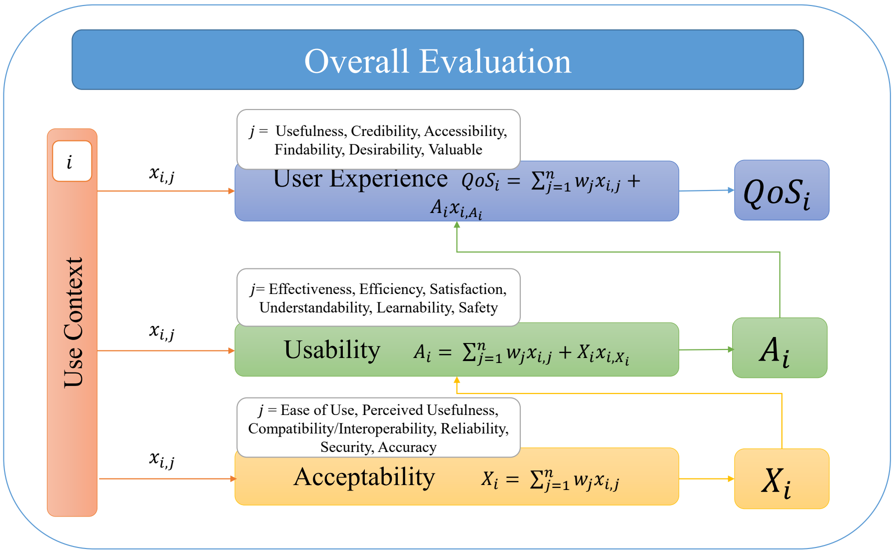


Fig. 6.12 Overall Evaluation. Reprinted from: [4].

where j indicates all the attributes of usability. By doing so, we are able to take into account the result obtained at the previous level, weighing it in accordance with its relevance in the current level;

3. proceeding towards the last level, we iterate the procedure, obtaining:

$$QoS_i = \sum_{j=1}^{n} w_j x_{i,j} + A_i x_{i,A_i} \tag{6.15}$$

where j indicates all the attributes related to the user experience and A_i takes into account the importance of the underlying levels.

The various steps of the modelling approach and procedure allow to quantify the QoS of an IoMT microservice, in particular, starting from the attributes set, the use context and graph that represents the networked resources of the s microservice, it provides a way to quantify a measure of QoS through a selection and clustering of the networked attributes and by applying the WSM methodology. The list of symbols and the pseudocode of the model are shown as the following Table 6.4 and Algorithm 1.

6.3.2 Performance Evaluation in a Complex Networked Scenario

The Figure 6.13, displays how a networked set of heterogeneous attributes that characterize the module of evaluation scheme proposed can be represented as N, an interconnected popula-

Algorithm 1 CoKnowEMe Evaluation Algorithm for IoMT Microservices. Reprinted from [4].

INPUT: s, a IoMT Microservice; microservice graph $G' = (R_k, E')$ with R_k set of Resources, E' set of edges; i use context; N the whole attributes population with elements $j \in N$.
OUTPUT: $G'' = (N', E'')$ evaluation graph, with N' set of vertices with $N' = N'_A \cup N'_U \cup N'_{UX}$ a merging of selected subset of attributes in function of i use context and s microservice and E'' set of edges; QoS_i quality of service value.
PHASE 1: "Selection and Clustering of Attributes Set".
1: INITIALIZE Acceptability Attributes Set $N'_A \leftarrow \emptyset$
2: INITIALIZE Usability Attributes Set $N'_U \leftarrow \emptyset$
3: INITIALIZE User Experience Attributes Set $N'_{UX} \leftarrow \emptyset$
4: GET the use context i
5: SET the $N' \subset N$ population of attribute.
6: SET N' into three clusters as the three different levels of evaluation, respectively N'_A, N'_U, N'_{UX}.
7: COMPUTE the values w_j and the weight x_{ij}, $\forall j \in N'$, with the use context i.
PHASE 2: "WSM method in complex graph for QoS computation".
8: SET G'' the Evaluation Graph as the weighted complex network graph $G'' = (N', E'')$ with N' population and E'' edges, with x_{ij} weights of the weighted directed links.
9: GET $p \in P$ the evaluation paths in $G'' = (N', E'')$, composed by a sequence of weighted edges among $j \in N'$, with $j \in N'_A$ or $j \in N'_U$ or $j \in N'_{UX}$ or $j \in N'_A \cup N'_U$ or $j \in N'_A \cup N'_U \cup N'_{UX}$.
10: COMPUTE the resulting sum of a sequence of weighted directed links that constitutes the path $p \in P$ mined from $G'' = (N', E'')$ with weights x_{ij}, $\forall j \in N'$ in the use context i, with values w_j, based on clusters to which nodes j of the path p belong to.
11: COMPUTE QoS_i quality of service value for $s \in S$, whose topology is expressed as $G' = (R_k, E')$, with i use context.
END

Table 6.4 List of Symbols.

Symbol	**Description**
S	Set of IoT microservices.
G'	Microservices' graph.
R_k	Set of resources.
N	Attributes population.
i	Use context.
$x_{i,j}$	Weight of attribute j in context i.
G''	Evaluation graph.
QoS_i	Quality of service related to the use context i.
N'_A	Set of acceptability attributes.
N'_U	Set of usability attributes.
N'_{UX}	Set of user experience attributes.
P	Set of evaluation paths.

tion of node. Here, it is considered as a sample of a complex networked graph that enables us to detect what kind of attributes in structural terms can have a key role more than another. The procedure is based on the WSM model, weighing up the contribution of each attribute and, as indicated in Figure 6.9, the attributes is considered capable to be interconnected through weighted links. Thus, a sample graph, having unit link weights, is considered by varying the size of the set of attributes jointly with the complex topology that interconnect the attributes in the graph. The topologies considered are three: Scale-Free networks (SF), Erdős–Rényi networks (ER) and Small-World networks (SW) (whose charactristics are described in Chapter 2). As shown in the Figure 6.13, varying the population size N, with a low value of N, both ER and SF display a skewed distribution. By increasing the size of the attributes, ER and SW present a more homogenized distribution, while the higher heterogeneous distribution is in the SF topology. These findings can drive the choice of suitable topology, under specific assumptions, and the detection of certain attributes that exhibit a role of hub in the network structure, and therefore under conditions of particular requirements at edge level (e.g., load balancing issue); this suggests that certain attributes cannot be excluded from the assessment. Moreover, by considering a heterogeneous, dynamic and complex approach, in line with the trend of the forthcoming 6G, the more realistic network structure SF is able to unveil hidden properties and roles of nodes that can change dynamically based on use context and environment and requirement conditions.

In addition, a performance evaluation on the quality-of-service measure is conducted, in function of the size of the attributes' population jointly with the variation of the clustering coefficient of the networked structure topology. To this aim, the Figure 6.14 shows that the QoS value increases with the increasing of the attributes' population size. The trend

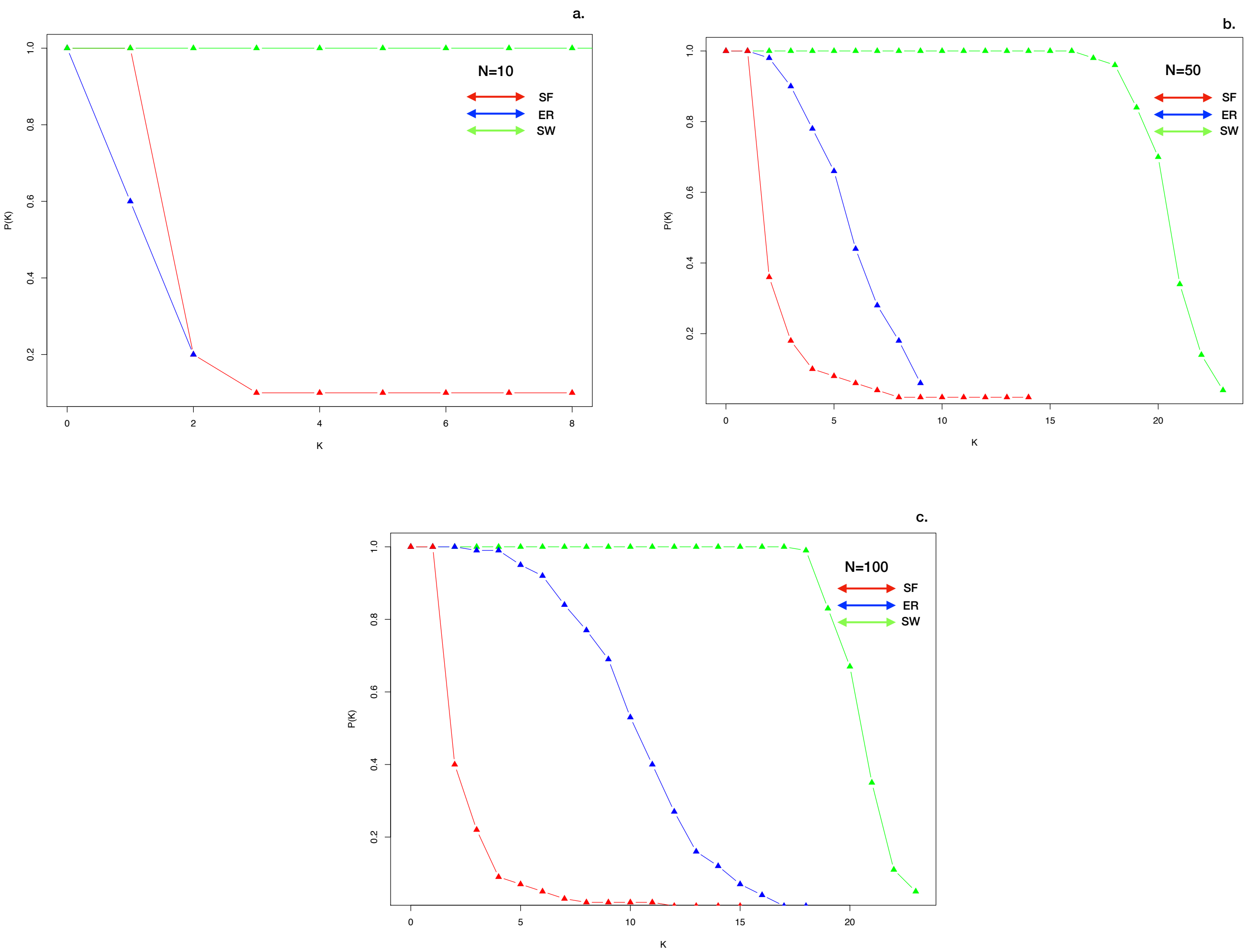


Fig. 6.13 Degree distribution of three different complex topologies of the networked structure of attributes. Reprinted from [4].

of QoS is shown in the case of two different topologies, the scale-free and the small-world structural network, assumed for both graphs, microservice's graph and evaluation's graph. The QoS depends on theoretical distribution of the values and weights of each attribute considered in the assumed sample. It is highlighted also the clustering coefficient by varying the population size in both cases. The clustering coefficient is a complex metric, representing a measure of the degree to which nodes in a graph tend to cluster together and quantifying the abundance of connected triangles in a network (as extensively described in CHapter 3). In the microservice graph the average clustering metric unveils the average measure for the resources nodes of the ratio of existing links connecting a node's neighbours to each other to the maximum possible number of such links. This is a key value to unveil the reuse of resources and how those nodes are connected together in groups, favouring small groups with high inter-links or big groups with high intra-links. This can impact the choice of the attributes' population size to better evaluate the quality of service of a microservice composed

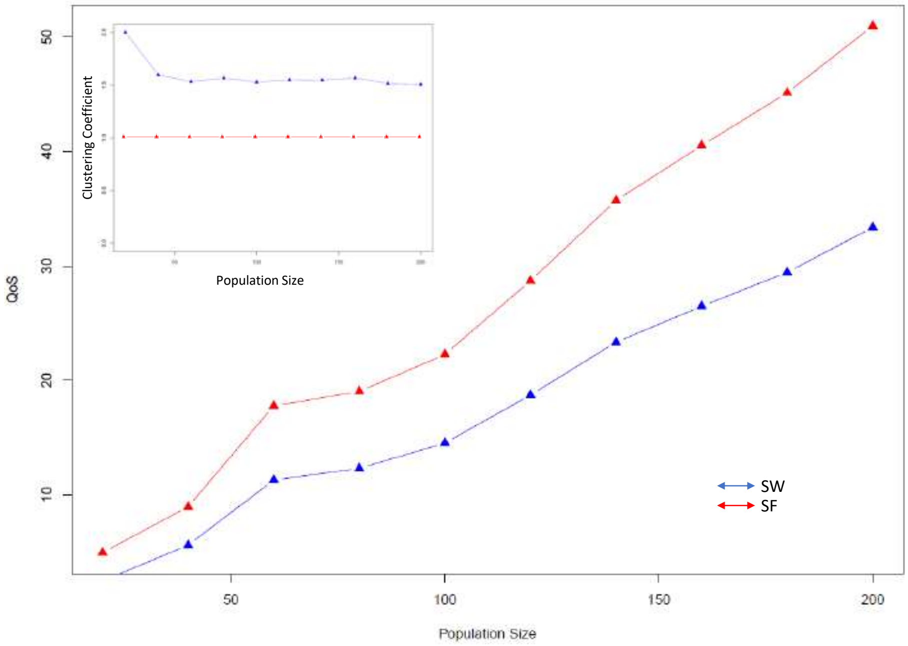


Fig. 6.14 QoS in function of the population size. Reprinted from: [4].

by interconnected resources. The small-world model (blue line) generates a homogeneous network; then the heterogeneous scale-free hypothesis (red line) and this shed light on that, even if the increasing of population size is valuable for both structures; with more inter-links of high value of heterogeneity as in scale-free topology, we obtain a higher level of QoS since it corresponds to a high level of reuse of resources.

6.4 Summary Remarks

This chapter describes complex approaches, in 6G networks, for both a node profiling and an evaluation scheme for IoMT microservices. The former allows nodes to acquire cognition ability, as the results of processes able to disentangle grades of knowledge on their connectivity and behaviours on multiple different channels by deepening into the investigation of structural and social aspects of the network, the collective dynamics of diffusion and competition, and the learning of belonging to various communities. The node profiling process step-by-step allows defining different aspects extracted from a complex networks analysis, in order to shape a profile which embeds macroscopic, microscopic, mesoscopic, dynamical and learning properties. The proposed profiling framework describes a set of interoperable abstract classes referred to processes which constitute a cognitive level for nodes and community of nodes in network, also detailing metrics and parameters, theory and analytical tools to study the coexistence of various type of interaction among nodes, and the

interplay of collective dynamics and the mesoscale organization.
The evaluation scheme is characterized by a multilevel architecture jointly with an analytical methodology based on complex system approach, and it is composed by different interoperable and chained modules that can assess several crucial aspects of the QoS. In particular, The IoMT services are represented as dynamical resources organized at edge level in a resource-oriented infrastructure enabling a self-organized connectivity and intelligent reusability of data and resources to deliver services. In accordance with this scenario the evaluation model is based on dynamic and adaptable features, represented, for each module, in terms of weighted attributes and sub-attributes, that convey the knowledge mined from the assessment analysis. Each individual evaluation layer can be used independently of the others or jointly with the other ones in an interoperable way. The entities of IoMT at the edge level can use the evaluation mechanism in an intelligent distributed way by enabling the reuse of the extracted output as collective resources and data.

Chapter 7

The impact of human-related factors in timely crisis response planning and in designing of policies for 6G applications

Overview: 6G will allow to turn into heterogeneous, cognitive and constantly-changing connected systems of things and people where collective behaviours and human-related factors are even more crucial. In this viewpoint, the digital traces left by humans are useful to observe the heterogeneous features of their attention and behaviours. Modelling the interplay between the collective attention and the co-evolving processes of awareness diffusion, and epidemic spreading on weighted multiplex networks is crucial to identify social network markers of interdependent collective dynamics, quantifying the role of human-related factors, as homophily and heterogeneity. The attention represents a social predictive marker of the awareness dynamics, unveiling the impact on epidemic spreading, for a timely crisis response planning. Collective behaviours and human-related factors are also crucial for services based on users' contributions and incentive mechanisms, such as Mobile crowdsensing. In this context, humans act as social sensors interacting on multiple and weighted layers related to various services. Novel statistical estimators to measure social honesty, Quality of Information (QoI) and users' behavioural reputation scores based on the evolutionary dynamics are crucial to introduce a Decision Support System (DSS) and a novel incentive mechanism by operating on the policies in terms of users' reputation scores, also incorporating users' behaviours other than quality and quantity of contributions. In both situations a data-driven approach based on the integration of different types of data, as user-generated data, (from Twitter and Google Trends o monitor the attention shift and from Waze for crowdsensing information) is crucial to digitally trace the human dynamics. [2]

[2]The models, results and discussion presented in this chapter are shown and published in these contributions: [120, 45]

7.1 Introduction

Human beings with their devices (from wearable to hand-held) and, consequently, their emerging behaviours and social dynamics will be increasingly central in future 6G networks, forming a sort of heterogeneous and aggregated things and playing an active role in the technical aspects and in the design of the networking functions, representing the interacting part that coexist in what can be considered as a complex socio-technical ecosystem.
In this viewpoint, the social networks and communication technologies can be exploited to achieve a systematic understanding of social collective dynamics, based on the complex networks paradigms that integrate weighted multiplex networks mathematical representation. They can be useful to consider the shifting of the public attention or the emergence of collective behaviours, which can guide the situational awareness and the timing of intervention strategies, impacting on emergency situations like the epidemics spreading and the designing of policies for people-centric applications based on human voluntary participation or contribution.
In the first part of this chapter, it is addressed the dynamical interplay of collective attention, awareness and Epidemics Spreading in the Multiplex Social Networks during COVID-19. The outbreak of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), a novel coronavirus, emerged in the city of Wuhan (Hubei, China) in early December of 2019, has posed a global public interest and it has raised concerns in most people worldwide on the future health and well-being[74][115][130]. The groups of cases of pneumonia of unknown cause detected in Wuhan was reported to the World Health Organization (WHO) on the 31st December 2019. Since then, besides China, cases confirmed with COVID-19 had also been detected in many other countries and territories [55][107], thus, from the city of Wuhan that has taken unprecedented measures in response to the outbreak, including extended school and workplace closures, also the other countries follows these strategies through various national responses to the pandemic, including measures such as lockdowns, quarantines, curfews and other restrictions (stay-at-home orders, shelter-in-place orders, shutdowns/lockdowns) aimed at preventing further spread of COVID-19. The global public attention to this issue can reflect people's interests and their propensity to acquire knowledge on COVID-19 with the aim at taking precautionary actions. In fact, to understand an emergency event, it is insufficient to rely on numerical reports based only on confirmed cases and the spatial spread [87], but it is needed adding more information, integrating knowledge and data on people's behaviours to quantify other dominant variables that can influence and impact possible future outbreaks.
In this chapter, it is proposed an analytical and data-driven rigorous investigation of what is the shape of response in terms of collective attention around a shocking and long-lasting event in which awareness and attention, in single and collective terms, jointly develop in an

interdependent way. It is investigated and measured which is the role and the weight of multiple and heterogeneous social ties, through the introduction of the weighted multiplex network, and the impact on the epidemic spreading. The impact of the attention and awareness on epidemic spreading is quantified, by introducing heterogeneity, both in terms of susceptibility and awareness, for optimally schedule effective crisis communications, facilitating timely crisis response planning, such as the decision of a time warning and quarantine. It is crucial to examine how the attention and the awareness arise and fade in different communities, affected in various times, impacting and influencing behaviours and decisions.

At the same time, the widespread diffusion and adoption of mobile devices (e.g., smartphones, tablets) with improved processing power and storage capacities, integrated with a wide variety of embedded sensors (e.g., GPS, gyroscope, camera, etc.) and the evolution of mobile communication technologies have led to a a wide range of applications [28, 33] that are part of the paradigm termed as Mobile Crowdsensing (MCS). MCS is a people-centric sensing system based on human voluntary participation or contribution about some phenomena in their surrounding environment. For example, human users with their personal mobile devices acquire local information (e.g., geo-spatial) and share their knowledge or measures with other users and communities in the network [28, 153, 77]. This largescale sensing paradigm leverages the collaborative approach and contributes to measure phenomena of mutual interest [28, 153, 145]. MCS is also an excellent example of the cyber-physical convergence phenomenon, leading to the Internet of People (IoP) paradigm [44]. Humans carrying mobile devices not only act as participatory or “social sensors”, gathering data, but they also interact with the physical and cyber worlds to accomplish changes [101, 8]. Thus, the dynamics of human behaviours play a key role in better understanding the complex behaviour of the cyber-physical-human world, putting people at the centre of this novel IoP paradigm. However, since participating in the sensing systems may incur costs and risks, common individuals are unwilling to participate and feed the system with their sensed data due to the lack of sufficient incentives or pushes towards cooperation. Consuming computational and communication resources of the personal smart devices, or privacy-related issues concerned with the provided location information when collecting data, are only some of these risks/costs. It becomes therefore crucial to motivate users with incentive mechanisms [28, 153]. It is important to observe how both the number (i.e., quantity) and the accuracy (i.e., quality) of reports assume a key role in the operational reliability of a MCS application [28].

In this context, here, it is proposed a game-theoretic methodology (see Chapter 4) in order to define a decision support system and the design of a novel incentive mechanism. Its definition is based on some statistical measures, that is the Quality of Information (QoI) and the reputation scores of each user in the network. These estimators are derived from the evolutionary dynamics of human sensing behaviours on a multi-layer social sensing framework, also quantifying the impact of homophily, network heterogeneity and multiplexity. In both situations, simulations results shed light on the coherence between the data-driven approach and the proposed analytical models.

7.2 The Dynamical Interplay of Collective Attention, Awareness and Epidemics Spreading in the Multiplex Social Networks during COVID-19.

The proposed framework, showed in Fig. 7.1, is aimed at quantify the interplay between collective attention and awareness dynamics, modelling them in two co-evolving and interdependent weighted multiplex social networks. Centering the analysis around the COVID-19, the geographical countries, represented as "communities", are those which have encountered the first case of COVID-19, within a fixed time window T. The T interval has been properly selected to extract the relevant spreading dynamics in different countries. Each first episode of COVID-19, officially reported in each selected geographical countries, here is stated as "event occurrence" E_{c_i} in T, with c_i, the country belonging to the set C of coun14tries selected. Following the data-driven and sampling approaches, presented in the Sections 7.2.3, the users, belonging to the communities, constitute the nodes which populate the first multiplex social network $\mathscr{M}_1$, namely the population-based multiplex. Each layer of $\mathscr{M}_1$ is referred to different kinds of interactions based on social networks relationships. For this reason, in $\mathscr{M}_1$, the interactions in the first layer between users, follow the theoretical scheme of a scale-free network [15, 36], with a power-law dependence of the degree distribution $P(k) - k^{\gamma}$, with the exponent $\gamma = 2$ that typically satisfying values around $2 < \gamma < 3$. Instead, the second layer of $\mathscr{M}_1$ follows the graph network extracted from the data-driven approach, showing virtual mined relationships for the same set of users. As detailed in the Section 7.2.3, large social networks communication by using Twitter datasets and Google Trends are integrated and analysed. A set of keywords K is constructed mining a set H of unique hashtags from Twitter, related to the sampled relevant users (see 7.2.3), and the set Q of the most popular terms of searches from Google Trends, in the fixed temporal window T. The elements of the subset H of K, represent the nodes of the population of the second weighted multiplex networks $\mathscr{M}_2$,namely the keywords-based multiplex network. In $\mathscr{M}_2$, each layer is a community-based level, and it is referred to a kind of interaction, defined as "co-adoption" relationships, based on the combined use of keywords by any users of that

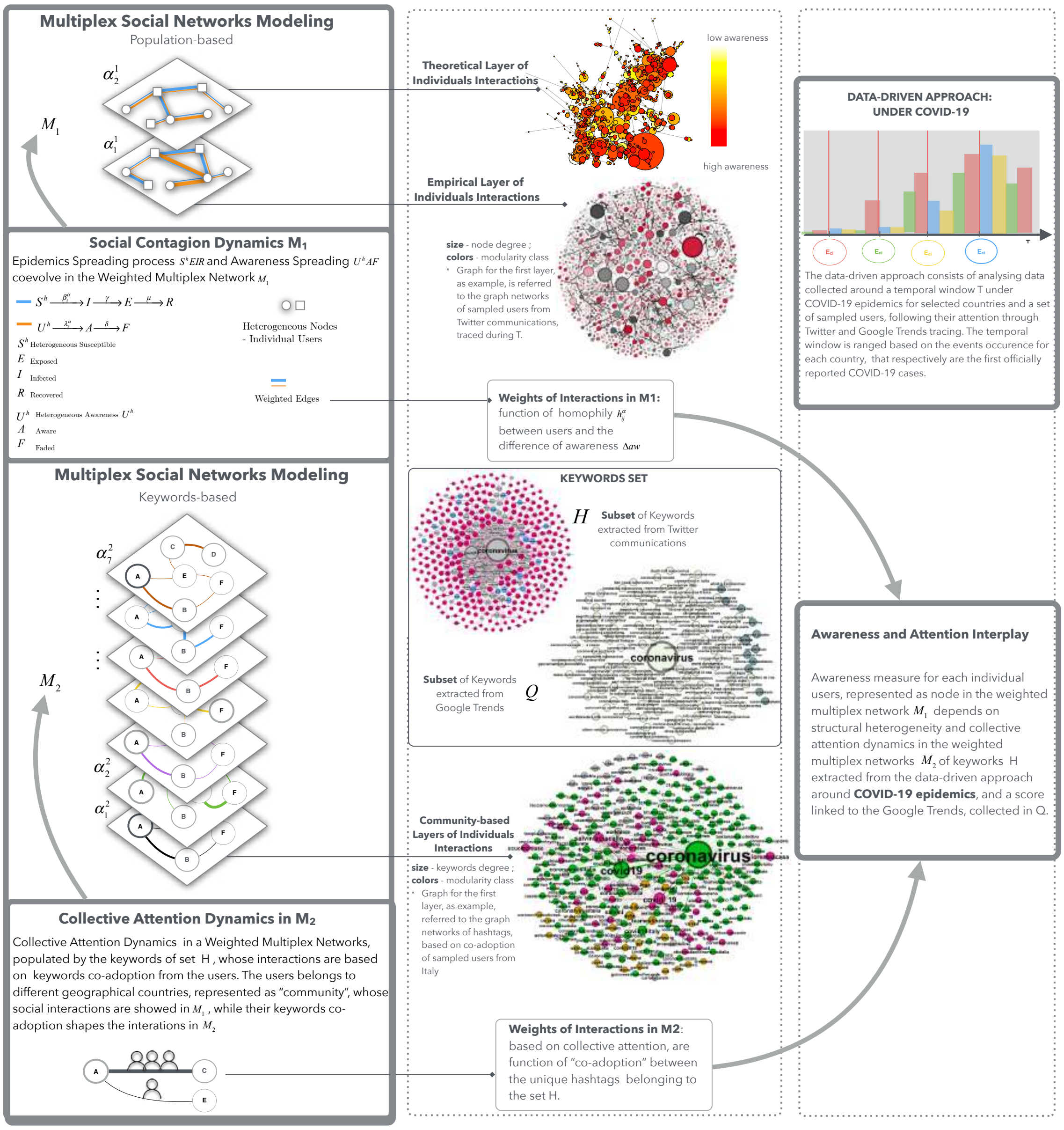


Fig. 7.1 From Modelling to Data-driven approach. Reprinted from [120].

community representing the layer, whose social interactions are explored in the multiplex network $\mathscr{M}_1$. Following, for each weighted multiplex social networks, it is detailed the mathematical representation, the definitions of weights, by highlighting statistical estimators and the metrics, which impact on the co-evolution of collective awareness and attention, and the impact on the epidemic spreading.

7.2.1 Multiplex Social Networks Modelling

Population-based

With regards to the first weighted multiplex social network, it highlights the importance of including multiple relationships between users, representing people of different communities as explained in the section 7.2. The first multiplex network $\mathscr{M}_1$, allowing to investigate how different network structure impact on the contagion dynamics, consists of two layers of interactions of the same set of users, a scale free-networks and a graph extracted from the data-driven approach. This makes us able to show a theoretical and an empirical interactions scheme to represent and investigate two types of virtual relationships for the same set of users. Let us consider the first weighted multiplex social network of $\mathscr{M}_1$ layers as defined in Chapter 3. The weights are defined as a function of the discrepancy of users awareness about the referred topic (Δaw) of COVID-19 and homophily (h_{ij}^{α}) (see Chapter 4 for the definition of homophily), namely the tendency of interacts with similar users.

Definition 1. *Weights of interactions in $\mathscr{M}_1$. Referred to the first multiplex network, the weights denoted as w_{ij}^{α} are given by:*

$$w_{ij}^{\alpha}|_{\mathscr{M}_1} = h_{ij}^{\alpha} \cdot |\Delta aw| + 1 \tag{7.1}$$

where $h_{ij} = 1/1 + \delta_{ij}$ is the homophily between nodes i and j. Homophily is defined as the tendency to associate and interact more with similar people (see Chapter 4 for the definition of homophily) and Δaw is equal to the absolute difference of awareness, $\left|aw_i - aw_j\right|$, between nodes i and j (see 7.2.1).

Keywords-based

With reference to the second multiplex network, it underlines the role of “keywords” as broker for users’ involved topics. The second weighted multiplex social networks $\mathscr{M}_2$, is populated with keywords as nodes, and the multiple interactions, different for each layer, between nodes as the “co-adoption” relationships. Each layer of this multiplex network is referred to each geographical country and the coexistence of several types of interactions among keywords based on the collective attention of individuals mined from social networks. Let us consider the second multiplex network of $\mathscr{M}_2$ layers $\alpha_2 = \{1, ..., \mathscr{M}_2\}$ and N_2 nodes $i = \{1, ..., N_2\}$. The set of nodes is the subset H of h hashtags, linked to the main topic under investigation. As explained below, in section 7.2.3, that set is created mining a set of unique hashtags from Twitter, used by any users in the fixed temporal window T. In T, based on a data-driven approach, a large corpus of datasets is analysed and the collective attention is digitally investigated and measured. As underlined for $\mathscr{M}_1$, $\mathscr{M}_2$ is described by its adjacency matrix, denoted by A^α with elements a_{ij}^α (see section 3.2 and 3.3 for further datails), and the weights of interactions are defined as follows:

Definition 2. *Weights of interactions in $\mathscr{M}_2$. Regarding to the second multiplex network, the weights are denoted as $w^\alpha_{ij|\mathscr{M}_2}$. To mathematically define the interaction weights, since they are based on the "co-adoption" relationships, as explained before, the concept hashtags "co-adoption" probabilities is introduces as the relative frequencies, that are: $p^\alpha_{h_ihj}$ which denotes the relative frequency of using both hashtags by users belonging to the community of the layer α of $\mathscr{M}_2$, and $p^\alpha_{h_i}$ as the relative frequency of using the hashtags h^α_i, by users belonging to the same community. In accordance to the latter, the weights of interactions in $\mathscr{M}_2$ are given by:*

$$w^\alpha_{h_ih_j|\mathscr{M}_2} = p_{h_ih_j} \cdot (p_{h_i} - p_{h_j}) \tag{7.2}$$

where, h_s with s in $\{1,2,...H\}$ are hashtags elements belonging to a subset of hashtags H, linked to COVID-19, the main topic under investigation.

Awareness and Attention Interplay

The awareness represents the acquired knowledge as a result of reasoning and understanding and, eventually, experiencing the epidemics. To capture the linkage between awareness and attention dynamics, which in turns impacts on the epidemics patterns, in this chapter it is assumed that the "awareness" measure, aw_i, for each node i belonging to users population of weighted multiplex network $\mathscr{M}_1$, depends on structural heterogeneity, collective attention dynamics on $\mathscr{M}_2$, and node properties [24, 96, 95]. Moreover,here, it is considered that the awareness measure has not change according to the layers, since awareness once acquired is the same in the different layers in which a user is involved. It can be influenced by the fading of interests on acquiring additional and correlated awareness, or verifying if it is fact-checked or misinformation based [122, 134]. The awareness gap between two interacting nodes in $\mathscr{M}_1$, impacts on the weights of links as detailed in section 7.2.1, in conjunction with the homophily value h_{ij}. In fact it is crucial to include the tendency to interact with similar people, through the introduction of homophily measure since strongly homogeneous groups tend to prefer contents that confirm their shared beliefs, polarizing rumours or misinformation. This phenomenon is defined as "echo chambers" effect which have a strict interplay with the spread of misinformation [134]. In presence of misinformation and highly homophilic clusters of users in social networks, it is very likely having fake news masqueraded as fact-checked contents[43].

Definition 3. *Awareness Measure in $\mathscr{M}_1$. Referred to the first multiplex network $\mathscr{M}_1$, the awareness measure for each node i, is denoted as aw_i, and it is given by:*

$$aw_{i_{t=T}} = (P_i|_{\mathscr{M}_1} \cdot \sum_{h \in H} H_h \cdot \sum_{q \in Q} \eta_q) + aw_{i_{t=t_0}} \tag{7.3}$$

where P_i is the multiplex participation coefficient which enable us to include the heterogeneity of the number of neighbours of node i across the layers in $\mathscr{M}_1$ [24]. The H_h represents the Shannon entropy of the hashtags h, mined from Twitter communications, belonging to the set H, which represents the population of nodes in $\mathscr{M}_2$ [24, 96] (see section 3.3 for the definition of multiplex participation coefficient and Shannon entropy), and η_q is a score, represented by the relative search volume (RSV), associated with the Google search popularity of terms q, elements of the subset Q extracted through Google Trends (see section 7.2.3).

7.2.2 Social Contagion Dynamics

Discussing the applicability of SEIR model in co-evolution with the UAF model for COVID-19.

The spreading of two processes in $\mathscr{M}_1$ is studied in co-evolution in the same multiplex network, referred to the epidemic and the awareness spreading [124]. Deciding to not disjoint the two processes makes it possible exploring the emerging complex dynamics highlighting the effect of the awareness dynamics, which is marked by cognitive limitations, on epidemic spreading, underlining also its impact on the acceptability of unprecedented restrictive measures due to the COVID-19.
A rising number of studies explored the model to fit mathematically the transmission of COVID-19, taking into consideration measures and strategies which reduces social mixing, modifying both the pattern within the population and the trajectory of the epidemics. Since the transmission is mostly driven by who interacts with whom, which can vary by age, location, contact, the protective measures of distancing have been designed to shift the social mixing patterns [115]. Given that, most of these limitations transform population mixing as well as human habits and the real social connectedness, consequently it becomes crucial the understanding to what extent the attention and the awareness in social networks can lead to behaviours in accordance with the provided reduction strategies. For that reason, currently, the increasing virtual connectivity [74, 43, 84], expressed in multiple layers, can marker the realization of a collective consciousness and impacting on the COVID-19 epidemic progression. In accordance with the recent epidemiological studies on parameters of the outbreak and propagation [148, 86, 61, 149, 148], the susceptible-exposed-infected-recovered

(SEIR) model [115, 148, 110] is considered in this approach as the epidemiological model for COVID-19, analyzing it in conjunction and co-evolution with the awareness social contagion process UAF [124], in $\mathscr{M}_1$. The SEIR model is generally used to model influence-like-illness, and it has been used to numerically analyze the evolution of the Severe Acute Respiratory Syndrome (SARS) in different social settings [110], [148], [61]. As observed in [88], the SEIR model fits mathematically with the nature of COVID-19 transmission. Moreover, in line with [115, 110, 86], the Exposed state (E) is a state in which individuals have been infected by the disease but cannot yet transmit it. Here, it is considered the assumption that asymptomatic cases represent a minor proportion of infectiousness compared with symptomatic cases, following the hypothesis in accordance with [115, 86]. In fact, although the contributions of asymptomatic or sub-clinical cases represent a pivotal point, and the question of whether such individuals are able to transmit infection remains unresolved at the time of writing, in accordance with the choice of temporal window that, and the aim at tracing the initial phase of rising the interest of collective attention around COVID-19, that cases are not considered here. To analyze the co-evolving dynamics of both epidemics and awareness spreading on $\mathscr{M}_1$ multiplex network, the proposed model rescues on the Dynamic Microscopic Markov Chain Approach (MMCA) (see section **??**) (see section 5.1).

Co-evolving Spreading Processes

In accordance with what defined in the previous section, here it is considered the key assumption that each node in $\mathscr{M}_1$ has a different awareness on COVID-19 as underlined in section 7.2.1. As a consequence, each node, will be heterogeneously susceptible to the epidemics spreading, since the awareness acquired has an influence on the behaviours of people, improving their knowledge about epidemics. Heterogeneity and awareness are introduced in order to describe the spreading scenario and extricate the complex co-evolution of the interdependence, from one hand, between epidemics and awareness and, from the other hand, between awareness and attention (see section 7.2.1). Two are the co-evolving spreading processes analysed in the first weighted multiplex network $\mathscr{M}_1$ (see section 7.2.1). The first process of epidemic spreading is indicated by S^hEIR and the awareness spreading process, coexisting and co-evolving with the first one, indicated as U^hAF. In this model, the awareness state is not directly correlated to the ensuring that users follow quarantine or other physical strategies. Although an increasing of awareness can infers a good behaviour in line with that strategical measures,influencing people to follow preventive measures as distancing interventions [124, 122]. Here, it has been intended as a knowledge and a consciousness that can contrast, for example, the misinformation diffusion about COVID-19. The node, in the F state, maintain the same awareness measure, but it has no interest in increasing its acquired knowledge on the phenomenon linked to the referred topic. The S^hEIR and U^hAF models, their reaction diffusion notations, the MMCA equations, and the epidemic thresholds have been widely described and defined in Chapter 5. For the sake of clarity, the meaning of the various states of the two spreading processes are explained in Table 7.1, a complete list of symbols with its fair meaning is summarized in Table 8.3, and the Probability tree linked to the MMCA method, representing the states and the transitions of S^hEIR U^hAF model.

Table 7.1 MMCA - States.

Status	Description
S^h	**Heterogeneous Susceptible** - Those who can contract the infection with a different infection rate. The nodes' heterogeneity, influenced by the awareness rate, impacts on the probability to have a transition in exposed status.
E	**Exposed** - Those who have been infected but cannot yet transmit it.
I	**Infected** - Those who contracted the infection and are contagious.
R	**Recovered** - Those who recovered from the disease.
U^h	**Heterogeneous Unaware** - Those who is unaware of the epidemic, or with minimum or wrong awareness. The probability to have a transition in Aware state is different for each node, depending on the impact of the collective attention, whom dynamics is analyzed in $\mathscr{M}_2$, on the weights of interactions of the multiplex network $\mathscr{M}_1$.
A	**Aware** - Those who is aware of epidemic, or who develop an awareness measure based on fact-checked information. The awareness measure depends on the collective attention on epidemics (see section 7.2.1)
F	**Faded** - Those who tend to decrease the attention on epidemics, or the interest to improve knowledge. The more susceptible are nodes that reach the faded state, the more vulnerable they become.

7.2.3 Data-driven Approach

Characterizing Collective Attention and Awareness interplay, under COVID-19

In this model, it is proposed a data-driven approach for evaluating the complex dynamics of co-evolving epidemics and awareness spreading, in function of the collective attention. To this aim, in the weighted multiplex network $\mathscr{M}_2$, as showed in section 7.2.1, user-generated data and searches are considered, respectively, by using a large corpus of Twitter communications datasets as listed in Table 7.3, and the most popular Google search terms, under COVID-19. The vast communications streams and searches, which still going on, enables us to monitor collective attention and, through the proposed framework, understand how it manifests itself under a real-world emergency event.

Table 7.2 List of Symbols.

Symbol	**Description**
T	Observed Time Interval.
t_i	Time sub-intervals considered.
DB_t	Datasets collected.
C	Set of locations c_i considered
E_{c_i}	Event occurrence with c_i the country belonging to C.
H	Set of unique hashtags h from Twitter.
Q	Set of the most popular terms of searches q from Google Trends.
K	Set of keywords $K = H \cup Q$.
U	Set of all users u.
N	Set of Sampled users.
A^{α}	Adjacency Matrix with elements a^{α}_{ij}.
$\mathscr{M}_1$	Population-based Multiplex Network.
$\mathscr{M}_2$	Keywords-based Multiplex Network.
aw_i	Awareness of a node i in the Multiplex Network $\mathscr{M}_1$
$w^{\alpha}_{i,j}\|_{\mathscr{M}_1}$	Weights of interactions between two nodes i and j in a layer α of the Multiplex Network $\mathscr{M}_1$
$w^{\alpha}_{h_i,h_j}\|_{\mathscr{M}_2}$	Weights of interactions between two hashtags h_i and h_j in a layer α of the Multiplex Network $\mathscr{M}_2$
$h_{i,j}$	Homophily between node i and node j.
p_{h_i}	Relative frequency to use the hashtag h_i.
p_{h_i,h_j}	Relative frequency to use both hashtags h_i, h_j.
P_i	Multiplex Participation Coefficient of node i in $\mathscr{M}_1$.
H_h	Shannon entropy of hashtag h in $\mathscr{M}_2$.
η_q	Score associated with the RSV from GTrends.
Y^{α}_i	Inverse Participation Ratio in the layer α.
s^{α}_i	Strength of node i in the layer α.
o_i	Overlapping degree of a node i.
Z_{o_i}	Z-score of a node i.
β^{α}_i	Heterogeneous Infection rate.
λ^{α}_i	Heterogeneous Awareness rate.
δ	Fading rate.
γ	Probability to transit from state E to state I
μ	Probability to transit from state I to state R
$q_i(t)$	Probability not being infected at step t.
$r_i(t)$	Probability not being aware at step t
β_c	Contagion Threshold.
ρ	Density of Infected nodes.

The whole temporal window considered T includes small ranges $\Delta t_{E_{c_i}}$ created as a consequence of relevant events happened, referred to the time in which the event has been officially reported in the c_i geographical countries considered, as detailed in section 7.2. In particular, seven short sub-intervals are taken into account, as listed in Table 7.4, in order to monitor attention patterns around the first officially reported cases of COVID-19 in each geographical country considered. Due to the observation constraints of Twitter API, in order to evaluate a large corpus of data in a long time window, data considered are extracted from [135, 78], whose statistics are shown in Table 7.3. These datasets were created searching for users who have applied hashtags related to COVID-19 such as: #coronavirus, #coronavirusoutbreak, #coronavirusPandemic, #covid19, #covid_19 [135, 78]. Each tweet in the datasets includes textual content, the author id and nickname, the creation time, if it was in reply to another tweet, whether it is a retweet and additional metadata. To identify all topic, all hashtags adopted have been extracted from tweets and both original tweets and retweets have been considered. In order to have a representation of the social network where the hashtags' diffusion takes place and to estimate the activity of users around COVID-19 emergency, users have been traced back, through the Twitter REST API, collecting additional information such as locations and number of Followers. As showed in section 7.2,in this model two interdependent weighted multiplex networks are considered in order to disclose the interplay between epidemics and awareness spreading, based on collective attention dynamics. The "Retweet-Mention-Reply" have been mined from a group of relevant users, that through the sampling approach, becomes the sampled set N of unique users, population of the weighted multiplex network $\mathscr{M}_1$. The subset of the most relevant hashtags H represents the population of the weighted multiplex network $\mathscr{M}_2$, restricting the available data to the unique hashtags used by users in N in all states under observation. For these two weighted multiplex networks, the analysis is focused on the collective dynamics and interactions of the population of sampled users N for $\mathscr{M}_1$, and hashtags belonging to the subset H for $\mathscr{M}_2$. In order to examine the attention dynamics, it is evaluated also the set Q mined from Google Trends considering the top 25 search keywords, having the relative search volume (RSV) score greater than 0, and in particular, among these, the related queries of searches about "COVID-19" in each geographical country for each time interval t_i in T. The pseudo code of the sampling and modelling approach and the social network marker detection is shown in Algorithm 2.

Sampling Approach

To construct the network's structure of the $\mathscr{M}_1$ weighted multiplex network (see section 7.2.1), we consider a population of users, interacting through a scale-free network in the first layer and a sampled weighted graph network in the second layer, mined from a selection of a

Table 7.3 Datasets used in this study

Dataset	Period	Users	Tweets Volume	Hashtag Volume
[135]	01-Dec-2019 -28-Feb-2020	41,914	60,160	10,986
[78]	01-Mar-2020 -11-Mar-2020	22,1928	526,791	135,664
[78]	12-Mar-2020	223,187	497,299	110,999
[78]	13-Mar-2020	569,099	994,611	238,367
[78]	14-Mar-2020	146,960	465,506	145,612
[78]	15-Mar-2020	245,218	464,396	142,924
[78]	16-Mar-2020	251,134	612,481	190,967
[78]	17-Mar-2020	356,262	834,944	249,083
[78]	18-Mar-2020	220,564	626,206	209,202
[78]	19-Mar-2020	284,981	855,845	267,057
[78]	20-Mar-2020	403,761	758,621	253,082
[78]	21-Mar-2020	393,600	881,955	256,816
[78]	22-Mar-2020	284,692	700,932	216,159
[78]	23-Mar-2020	255,576	658,225	229,724
[78]	24-Mar-2020	297,203	620,860	226,176
[78]	25-Mar-2020	278,293	684,556	245,815
[78]	26-Mar-2020	195,235	881,278	209,368
[78]	27-Mar-2020	302,559	664,120	239,108
[78]	28-Mar-2020	271,370	582,055	211,808
[78]	29-Mar-2020	227,820	564,141	204,568
[78]	30-Mar-2020	285,320	586,262	224,554

Table 7.4 Time windows

t1	12-Dec-2019 - 31-Dec-2019
t2	01-Jan-2020 - 15-Jan-2020
t3	16-Jan-2020 - 31-Jan-2020
t4	01-Feb-2020 - 15-Feb-2020
t5	16-Feb-2020 - 29-Feb-2020
t6	01-Mar-2020 - 15-Mar-2020
t7	16-Mar-2020 - 30-Mar-2020

Algorithm 2 : The Interplay of Collective Dynamics in Multiplex Social Networks

Input: Event in T (as COVID-19); Datasets collected (DB_t); δ_{ij}, μ, δ,γ.
Output: $\mathscr{M}_1$,$\mathscr{M}_2$, aw_i,β_c, ρ_I in T.
1: Phase 1: Sampling Approach.
Sampled Set of Users $N \leftarrow \emptyset$
Sampled Set of Hashtag $H \leftarrow \emptyset$
Sampled Set of Queries $Q \leftarrow \emptyset$
2: Set $t_i \in T$ filtering DB_t by Tweets' creation time.
3: $\forall t_i \in T$, $\forall u \in U$ collect data about users through Twitter API .
4: $\forall t_i \in T$, $\forall c$ collect queries through GTrends API.
5: $\forall t_i \in T$ and $\forall u \in U$ calculate "activeness" and "connectedness" of users, considering the number of tweets n_{T_u} of a user u and a threshold T_T, the number of followers n_{F_u} of a user u and a threshold T_F.
if $\forall t_i \in T$**,** $n_{T_u} > T_T$ **AND** $n_{F_u} > T_F$ **then** $N = N \cup u$.
6: $\forall t_i \in T$ and $\forall u \in N$ retrieve Hashtags from Tweets in DB_t.
7: Filter N by location, c, and consider H_c set of retrieved Hashtags.
8: Create $H = H_1 \cap H_2 \ldots \cap H_c$, and $Q = Q_1 \cap Q_2 \ldots \cap Q_c$ from the most frequent queries $\forall t_i \in T$.
9: Mining of the "Retweet-Mention-Reply" graph of the users in N and the c "Hashtags co-adoption" graphs of the hashtags in H.
10: Calculate the relative frequency of the hashtags in H, p_h.
11: Phase 2: Multiplexity - Social Contagion.
12: Set N as N_1 population of $\mathscr{M}_1$.
13: Set the "Retweet-Mention-Reply" graph of the users in N as $G_{\alpha=1}$ and a Scale-free networks as $G_{\alpha=2}$, with G_α graphs of the $\mathscr{M}_1$ with $\alpha = 1,...,\mathscr{M}_1$ layers.
14: Set H as N_2 population of $\mathscr{M}_2$ multiplex network and the "Hashtags co-adoption" graphs of the users in N as $G_{\alpha=c}$, with G_α graphs of the $\mathscr{M}_2$ with $\alpha = 1,...,\mathscr{M}_2$ layers.
15: $\forall i \in N_1$ in $\mathscr{M}_1$ calculate k_i, o_i, P_i, Z_{o_i}.
16: $\forall h \in H$, in $\mathscr{M}_2$, calculate calculate k_h, o_h, H_h and $\forall q \in Q$ a score η for each c location.

17: $\forall i \in N_1$,in $\mathscr{M}_1$, calculate aw_i, w_{ij}, s_i^α, Y_i^α
18: Calculate w_{h_ihj} in $\mathscr{M}_2$.
19: $\forall i \in N_1$, in $\mathscr{M}_1$, assign to i one of the initial states SU - SA - IA.
20: at time step t, calculate λ_i^α, β_i^α, $q_i(t)$, $r_i(t)$.
21: MMCA method.
22: Calculate β_C,ρ_I in T.
23: Phase 3: Social Network Marker.
24: detect the emergence of the first event case E_c^I, and $\forall c$, detect E_c,R_t^c, SM_t^c, and calculate the delays $D_{R_t^c E_c^I}$, $D_{cm_t^s E_c}$ and $D_{R_t^c E_c}$.
25: $\forall c$, calculate aw_r, and , its growth rate $\pm aw_r(\%)$ as the social network marker impact.

set of interacting nodes on Twitter and based on the datasets analyzed [135],[78]. Although a straightforward way for an understanding of attention dynamics is to gather data from as many users as possible, it is fundamental to apply a sampling approach, to identify the most influential users and their relationships, preserving the topological properties of the original structure. This set of sampled users, are that more likely can trigger awareness diffusion giving an impact on epidemic spreading. An ideal sample set should consider users with the following features[69]:

- *Activeness*: the sampled set contains users who tend to tweet with hashtags linked to COVID-19, at a relatively high frequency during the time of interest T. Who have the tendency to maintain a high level of interest on topic through time, presuming that they are more likely to be active in the spreading dynamics. A user is included in the sampled set N if has posted a number of tweets greater than a threshold T_T in each time window t_i.

- *Connectedness*: the sampled set includes users who tend to be actively connected with other users showing their capability to cover a broader set of users, namely those who actively join into the common interests of many other users. The threshold T_F of users' number of followers is defined and only who has a "followers_count" value greater than T_F is added to the set N of sampled users .

Evaluating both the activeness and the connectedness it is possible to select the most popular users that are at the same time, the most active within the time period considered, avoiding missing content or activity gaps over time.

Comparison with a null model

An interesting pivotal point is bringing together the nature of the extraordinary event, such as the one represented by COVID-19, with the usual emerging dynamical patterns from social networks. Without any doubt, this epidemic is not a common health emergency. In terms of collective attention, the interest is spread over time and continues to involve the population as a result of strategical measures and an uninterrupted updates on the data and the evolution of spreading itself [84, 131]. To evaluate if the emerging dynamical patterns is caused by an interplay between polarized attention and awareness on epidemics, or by a change on individual interests dynamics, rippling with a similar shape in other cases, the observed dynamics is compared with that one based on a null model. The null model is created for a fixed set of users, comparable to those considered in this model, in a period of time, prior to COVID-19, and comparable with the time interval T, during which the same set of data

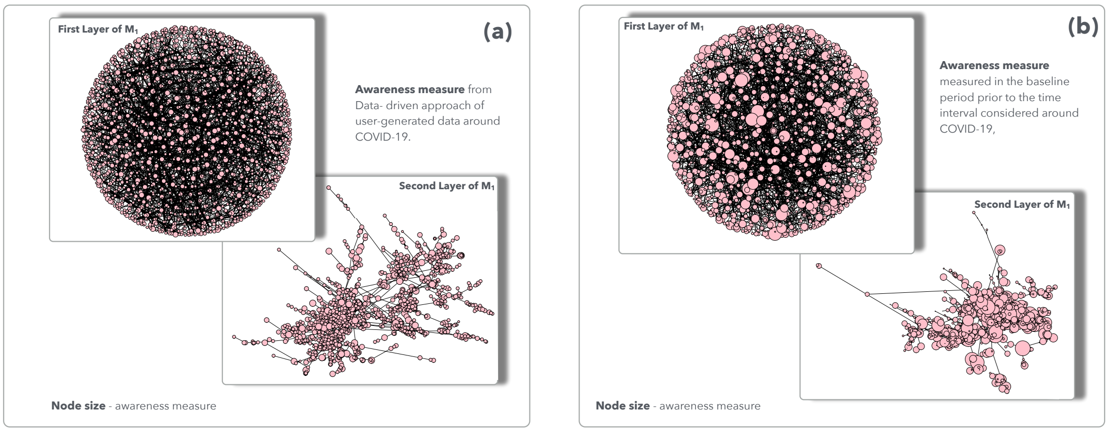


Fig. 7.2 Awareness distribution on Multiplex Network. Reprinted from [120].

7.2.4 Performance Evaluation

Simulation Setup

Simulations have been carried out considering two weighted multiplex networks, respectively $\mathscr{M}_1$ and $\mathscr{M}_2$ as explained in Sections 7.2.1 and 7.2.1. Firstly, in the $\mathscr{M}_1$ weighted multiplex social network, it is considered the key role of multiple relationships among users, which represent people of different communities, referred to the seven states considered in the data-driven approach. In $\mathscr{M}_1$ the population is $N = 1461$ users, representing the users of the sample extracted as showed in Section 7.2.3. In the first layer the interactions are based on the graph network extracted from the data-driven approach, showing virtual relationships for the sampled set of users, while in the second one the interactions follow the theoretical scheme of a scale-free network [15, 36]. Data were collected through the Twitter API and GTrends API. To build the model, do computation and obtain our results we used the programming language R and the IDE RStudio. The figures were generated thanks to the package Plotly and the software Gephi [116], [133], [128], [20].

Numerical Results

Fig. 7.2, displays how the structural heterogeneity of interactions and the heterogeneous distribution of the awareness characterize the model, depending on the parameters of the multiplex network, considering the features of each node regarding the two co-evolving spreading processes around epidemics and awareness dynamics. Each node belongs to the

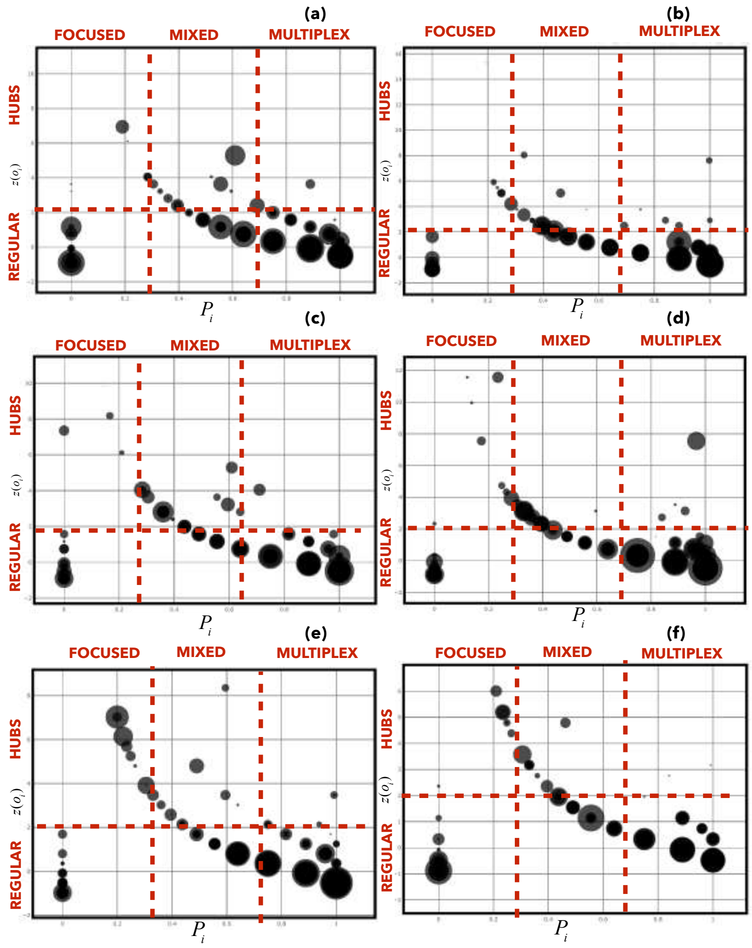
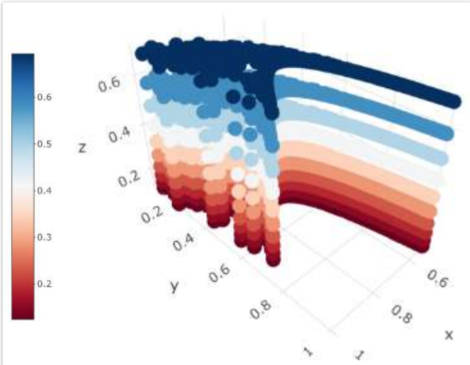


Fig. 7.3 Roles of nodes. Reprinted from [120].

sampled users set extracted from the data-driven approach, and it owns a distinct awareness measure, such a consciousness that allows to react differently to the epidemics, producing a different susceptibility. Following the assumption of the proposed model and the data mined, in panel (a) of Fig. 7.2 here it is highlighted the heterogeneity distribution in network structures for the case of awareness measures based on multiplex parameters and user-generated data mined from Twitter and Google Trends (see details in both Sections 7.2.1 and 7.2.3), in comparison with the awareness measures based on baseline statistics, as showed in panel (b). It is notable how the multiplex network exhibits a heterogeneous distribution of awareness measures in panel (b), as a result of a global attention distributed in various clusters of different topics. Instead, consequently to the occurrence of an emergency event, as COVID-19, it acts as a shaking force that polarizes the collective attention shaping the awareness distribution in multiplex network $\mathscr{M}_1$ into a more homogenized structure since the nature of the event rules the choice on what to pay attention[69]. This effect produces a



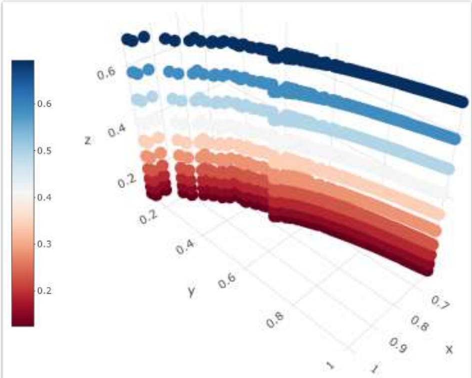


Fig. 7.4 $\lambda - \beta - \rho$ Phase Diagrams. Reprinted from [120].

decreasing in randomness and an increasing of a collective process. In accordance with the assumption of the model, the awareness measures distribution acts on the interactions weights in conjunction with the homophily measure, impacting on the heterogeneity in terms of node susceptibility against the epidemics, and in terms of infection and awareness rate, shaping also the structural heterogeneity of the degree distribution in the $\mathscr{M}_1$ weighted multiplex network.

In each plot of Fig. 7.3, the curves correspond to the different values of the distribution of P_i, the participation coefficient of node i in the weighted multiplex network $\mathscr{M}_1$ in function of the Z-score of the overlapping degree of the node, representing its overall importance in terms of number of edges, with the aim at introducing a classification of nodes in terms of its properties into the multiplex network, highlighting also the awareness distribution, showed as size of nodes. Moreover, the panels (a)-(c)-(e) are referred to the data-driven awareness measures, the panels (b)-(d)-(f) to the baseline statistics, and in both cases from the top to bottom panels the homophily measures among nodes decreases [23, 24]. Representing each node as a point in the plane $P_i - Z_{o_i}$, by considering the multiplex participation coefficient and the variation in function of Z_{o_i}, it is possible considering the six classes of nodes as

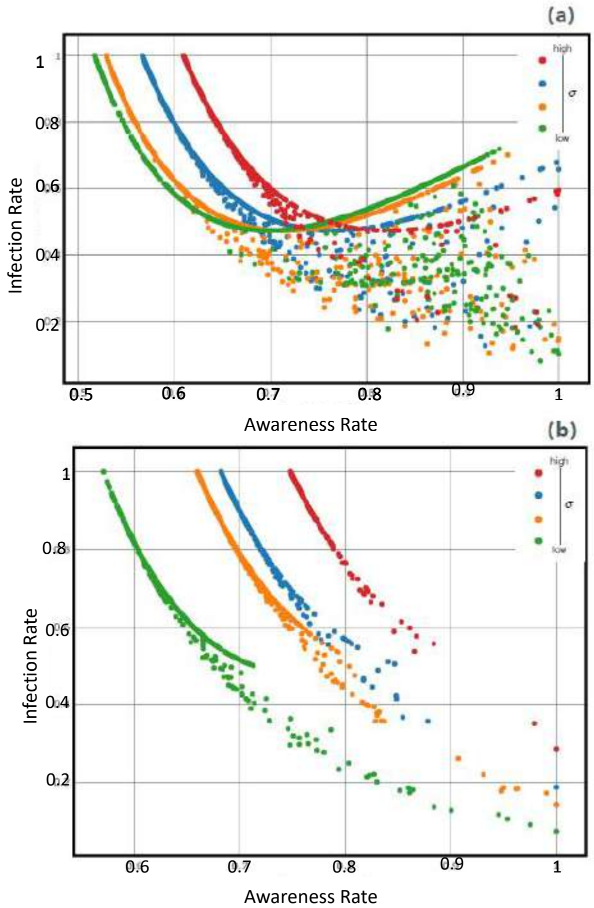


Fig. 7.5 Diagrams $\lambda - \beta$. Reprinted from [120].

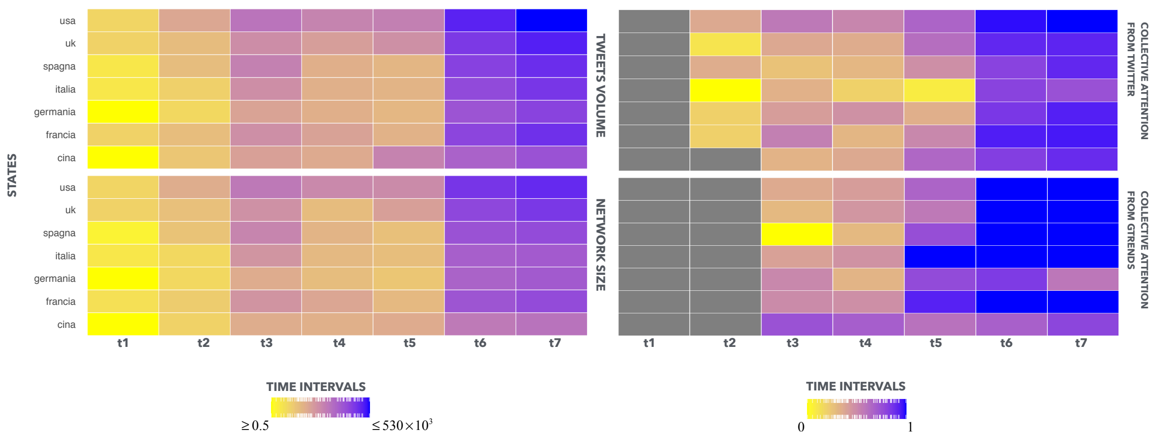


Fig. 7.6 The changes of collective attention from user-generated data during time intervals around COVID-19. Reprinted from [120]

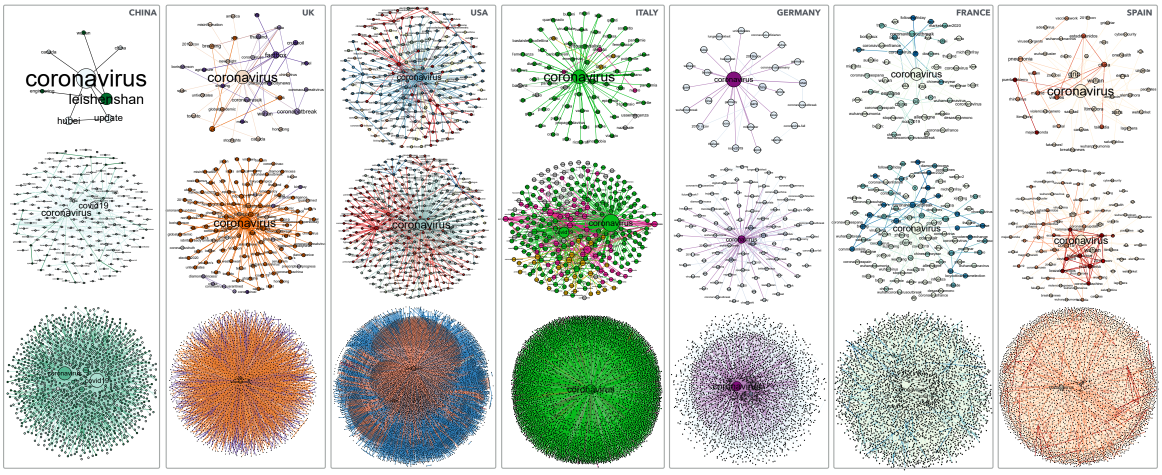


Fig. 7.7 Collective attention and Hashtags co-adoption shifting in time intervals around COVID-19. Reprinted from:[120]

highlight in Fig.7.3, varying homophily measures, showing the awareness distribution. In both cases, it is observable the greatest randomness effect, in terms of awareness distribution, in plots referred to the baseline statistics, (b)-(d)-(f). In the case of (a)-(c)-(e) plots, the more participatory the nodes are, the more they acquire a greatest value of awareness, especially in the case of high homophily among nodes (as showed in plot (a)), disclosing this trend especially for regular mixed and multiplex aware nodes. Decreasing homophily values, from (c)-(d) to (e)-(f), respectively referred to awareness data-driven and that one based on baseline statistics, it is evident with an increasing of P_i values, a heterogeneous distribution of awareness in the plane $P_i - Z_{o_i}$, and a higher density of hubs nodes, in focused roles with higher awareness values. This trend is more evident in the case of awareness based on data and it means that, decreasing the homophily, it is possible to find out a higher presence of focused hubs, more aware in the case of awareness based on data than in baseline statistics case, since the latter suffers the effect of attention randomness. As a result of a collective process around an extraordinary event, in (e) plot it is shown this effect, showing how the most aware nodes are either more participatory or more central.
Fig. 7.4 displays the phase diagram in the plane $\rho - \beta - \lambda$, according to the co-evolving processes of epidemics and awareness in the weighted multiplex network $\mathscr{M}_1$, and its interdependence with the collective attention dynamics in $\mathscr{M}_2$. Both panels show how the double heterogeneity, in terms of infection and awareness rates, allows delaying the contagion outbreak and reducing the density of infected nodes. An increasing of awareness rate results in a decreasing of infection rate up to a specific value of awareness rate, as showed in (a) plot, in which the awareness measures for each node derived from the baseline statistics in a scale-free structure. This means that the remarkable shape is due to the dependence of the

heterogeneous susceptibility on the awareness and, when the probability of acquiring more awareness exceed a threshold, this leads to a more probable shift in attention in correlated topics, resulting in an increasing of ρ, the density of infection. Differently, in the (b) plot of Fig. 7.4, which is referred to the case of awareness measures derived from data, that effect vanishes due to more homogenized trend of awareness values around topic linked to the extraordinary event occurrence, and to an increasing of awareness rate corresponds a decreasing of the epidemics trend.

Fig. 7.5 shows the trend of infection rate in function of awareness rate, varying the homophily value. The homophily, representing a human-related factor enables the structural investigation of how the connections are forged in social networks. For that reason, varying its standard deviation associated to traits, that define the similarity between a pair of nodes showing the resulting trend in the plane $\lambda - \beta$, it is possible considering the two cases of the baseline and the data-driven in reference to the awareness of the users. In the plot (a), referred to the baseline case, by decreasing the homophily (from green curve to red curve), up to a threshold, the increasing of awareness rate have a minor impact on the infection rate since the population interests are distributed around different topics and the collective attention is shaped as a more heterogenous structure. Differently, in (b), that is based on data mined from Twitter communications under COVID-19, by increasing the awareness rate, a decreasing in infection rate is is observable. By decreasing the homophily, the awareness impact is lower than the baseline case, unveiling that the collective dynamics of attention and awareness is more homogenous around the COVID-19.

Fig.7.6, summarizes the collective attention dynamics, during temporal window T, divided in seven-time intervals, as detailed in Table 7.4, around COVID-19. The heatmap is based on user-generated data from Twitter communications and queries from Google Trends (see Section 7.2.3). This plot allows for comparing different network metrics, such as tweets volume, networks size, collective attention from Twitter and Google Trends, ranging the different normalized values into coloured bands. The different colour shades in the bands for each geographical state considered, in reference to each time interval, underline the changes in time, in correlation with the red points, that indicates in which time interval falls the first case of COVID-19 officially, reported to WHO. The grey bands point out the lack of values on collective attention, in the range that covers t_1 and t_2. Following the assumption of the model, this puts in evidence that the sampled users set includes users which have a role in the rising of collective attention and consequently in the awareness and epidemics dynamics. For that reason, although there are collective attention data on COVID-19 in t_1 and t_2, these are not referred to relevant nodes in dissemination. Moreover,the red points indicate the time in which each state goes from being observer to affected community. Thus, considering the tweets volume and the network size metrics, it is evident a shifting in trend after t_6, detecting a delay of two time intervals from the time when the majority of events occurred. Focusing on the collective attention metrics, stated for sampled set of users, the patterns of collective dynamics is highlighted zooming the shape of reaction in response to the events occurred. This shows a growing interest, that although it is not free from delay, follows the timing of COVID-19 appearance.

Fig. 7.7 illustrates for each state the evolution of the collective attention, mined from the analysis of user-generated data from Twitter communications, in different crucial time intervals, t_3, t_5 and t_7, that fall within the temporal window T. The representation of the weighted graph networks captured by the use of different co-adopted hashtags, is filtered following the data-driven approach as underlined in Section 7.2.3. The Fig. 7.7 shows, looked at it from top to down, the dynamical evolution of co-adoption around the topic, reflecting the scattered attention among various co-adopted hashtags linked to COVID-19. It highlights a quantitative measure of users' attended topics, capturing it close to the events in t_3, after the events happened in t_5, and finally, when the collective attention get up to speed up to t_7. The graph networks populate the layers of weighted multiplex networks $\mathscr{M}_2$, following the assumption of our model (see Section 7.2.1), introducing quantitative dynamical statistical parameters referred to the collective attention impacting on the dynamical behaviours of the users in the weighted multiplex network $\mathscr{M}_1$. This figure exhibits the rising of the digital traces allowing for exploring the users' interest into co-adopted various hashtags about COVID-19, representing the willingness to expose their attention to as many people as possible, thus, increasing the likelihood to give a boost to a collective process.

The Table 7.5 lists various information about the response time, in terms of both strategical measures and social collective attention, the occurrence of COVID-19 cases and the awareness reactivity to the emergency occurrence, also with the impact of a social network marker. For the purpose of comparing the public response to the topic around COVID-19 across countries selected, there is a comparison between the time of the cases reported to WHO for each country and the peak response in terms of attention, from Twitter and Google Trends, as a result of the analysis of user-generated data. The "Delay from China reported first case" filed represents the delay of the first response of the collective attention from the China reported first case, the "Starting lockdown-quarantine measures", which is the time when the countries decide to start the strategical measures, and the "Delay of lockdown measures from the reported internal cases for each country". Moreover, the introduction of the "awareness reactivity" awr_i, for a country i represents a statistical parameter which quantify a measure of responsiveness based on information entropy H, computed on the basis of data extracted from social media platforms considered, as Twitter and Google Trends, over the elapsed time

Table 7.5 Response Time and Awareness Reaction Time

States	**China Reported to WHO**	**Internal cases reported to WHO**	**First Peak Response (from Twitter)**	**First Peak Response (from Google Trends)**	**Delay from China Reported First Case (days)**	**Start Lock-down Measures**	**Delay of lock-down from first internal case (days)**	**Awareness Reactivity**	**Awareness Reactivity (+/-) social marker impact (growth rate %)**
CH	31-Dec-2019	-	13-Jan-2020	17-Jan-2020	13	23-Jan-2020	23	0.93	-26%
USA	-	23-Jan-2020	04-Jan-2020	19-Jan-2020	4	(19-24)-Mar-2020	(56-61)	(0.70 - 0.65)	+46% - +41%
UK	-	01-Feb-2020	13-Jan-2020	20-Jan-2020	13	23-Mar-2020	51	0.73	+39%
IT	-	31-Jan-2020	13-Jan-2020	21-Jan-2020	13	9-Mar-2020	38	0.57	+49%
DE	-	28-Jan-2020	13-Jan-2020	19-Jan-2020	13	23-Mar-2020	55	0.45	+28%
FR	-	25-Jan-2020	13-Jan-2020	20-Jan-2020	13	17-Mar-2020	52	1	+22%
ES	-	01-Feb-2020	01-Jan-2020	20-Jan-2020	1	14-Mar-2020	42	0.86	+258%

from first reported case of each country. This parameter weighs the speed at which a country knowingly took notice of the emergency, deciding to start strategical measures, to assess the optimal policies while minimizing the output costs of the protective strategies. High values of awareness reactivity awr_i means that there was a fast response to the emergency, that matches high entropy of content shared in online social media platforms and collective attention dynamics, and a high alertness impacting the timing of strategical safety measures. Moreover, taking into consideration the elapsed time between the first peak of the collective attention from the first reported case for each country, the awareness reactivity is obtained by subtracting this delay from the other delays considered. As indicated in the last column, the resulting value is expressed as an awareness reactivity growth rate. In the case of China, a percentage in decrease of awareness reactivity due to the fact that it is the country that has the first peak of collective attention response after its first case reported in WHO, differently from the other countries selected. This value represents the impact on the awareness reactivity, finding out the speeding up of the preparedness and responsiveness that would have had if it had considered the effects of the collective attention and awareness dynamics, that is a rising social measure of the public interest around an emergency that would soon have arrived.
The figure 7.8 shows the awr_i changes and the social marker impact on its growth percentage on the different time windows considered (see Table 7.4) in function of the collective attention extracted from the data-driven approach. The figure graphically displays the variation of the awr_i with regards to COVID-19 based on awareness dynamics, considering the impact of the social marker (black line) and not (red line). In particular, the figure represents a prediction of how the awr_i for each state would increase or decrease, graphically representing the impact of the social marker, if the attention peak would have been in different time intervals. As in cases b), c), d), e), f), g) in the time intervals previous respect to the first reported case, when the states are in the condition of observer, the social marker's effect produces an increase in awr_i and, when the states become affected, causes a decrease over time. The only exception is represented by China (a) which is affected in the whole-time interval under investigation and has a peak of attention that is always legging behind the first reported case to the WHO. In this case, taking into consideration the effect of the social marker, the awr_i decreases from the first time interval.

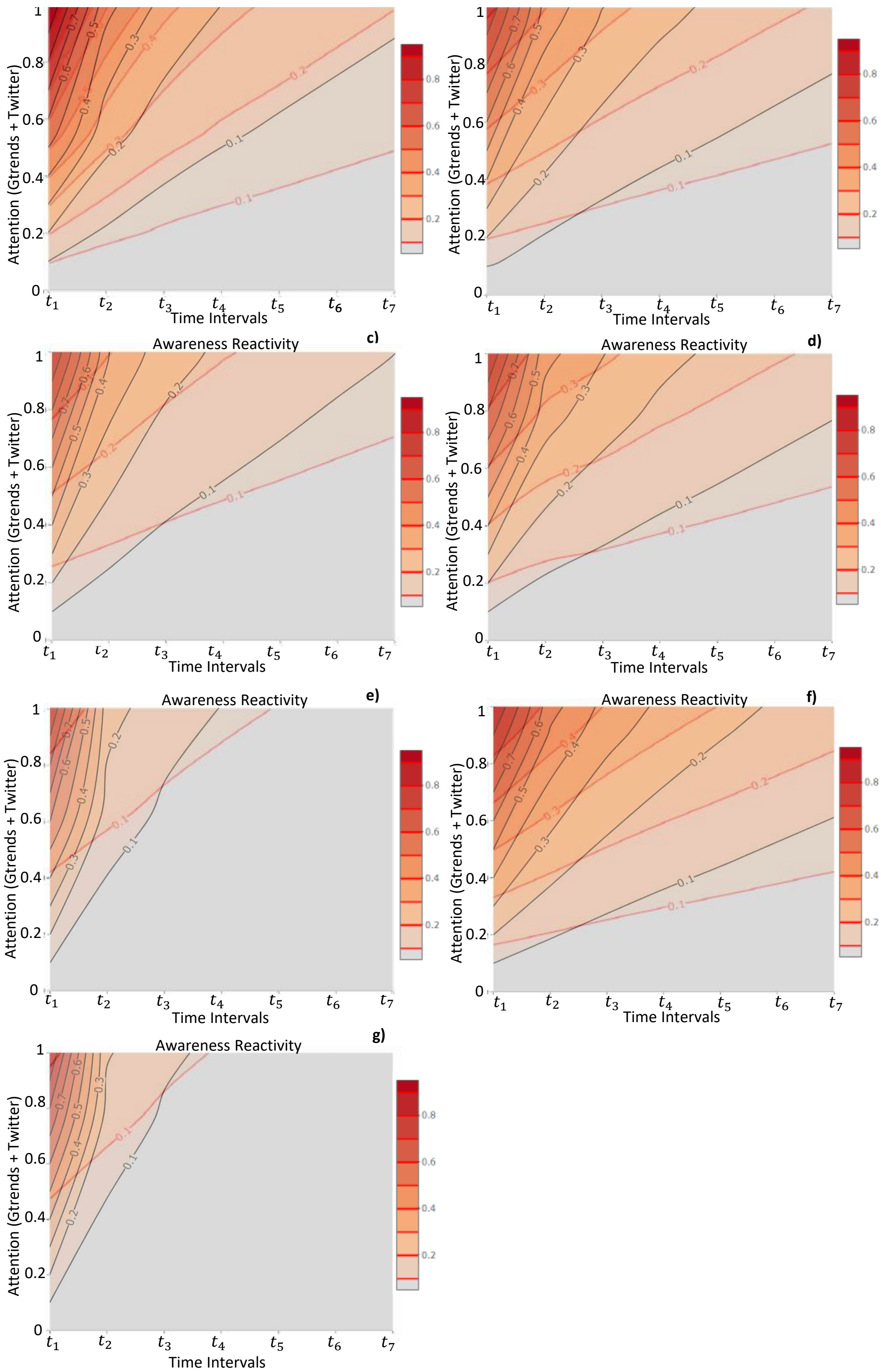


Fig. 7.8 Social marker impact on the Awareness Reactivity Growth Rate. Reprinted from: [120]

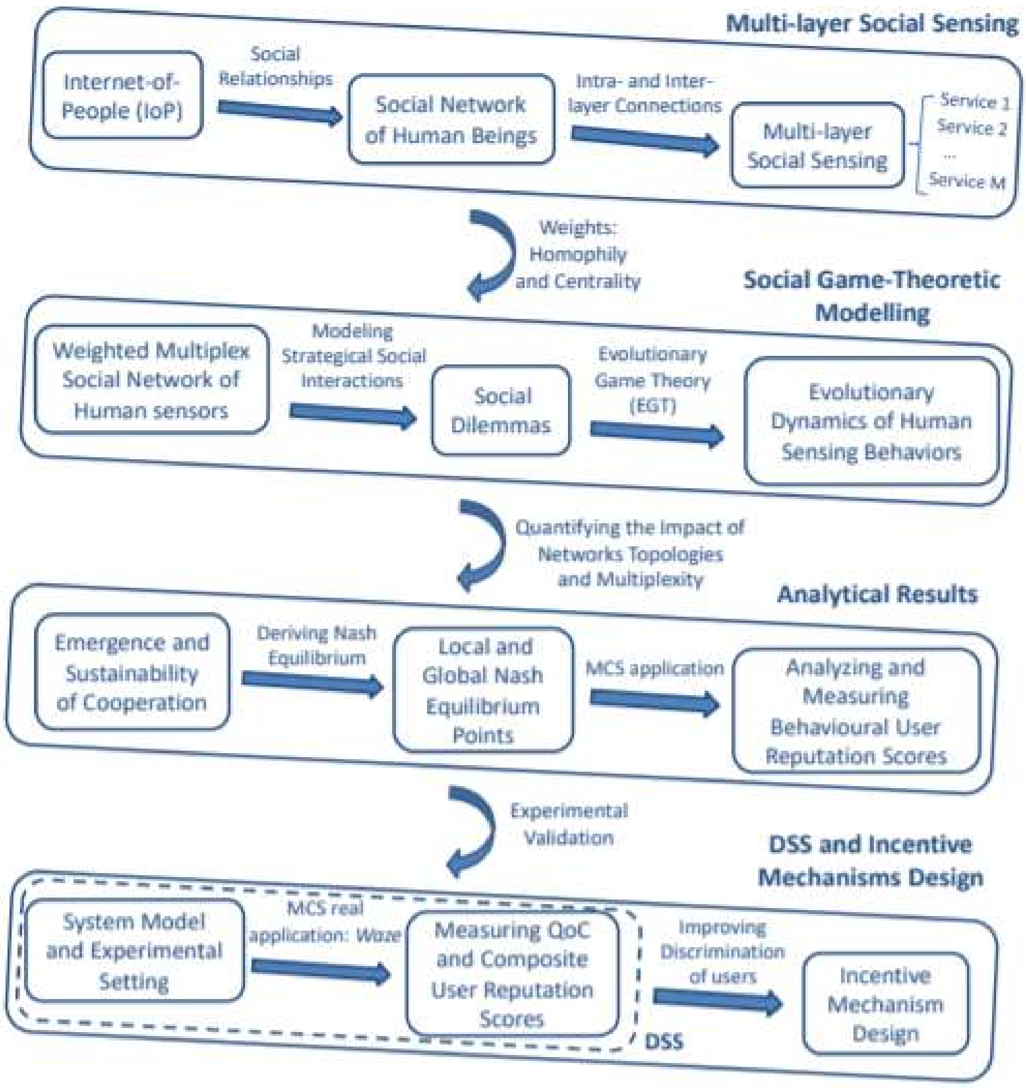


Fig. 7.9 Social Sensing and Cognitive architecture. Reprinted from: [45]

7.3 A Novel Methodology for Designing Policies in Mobile Crowdsensing Systems

The considered scenario is a typical urban sensing application, where a particular urban area is divided into multiple sensing regions. In each of these regions, there is a population of users along with their smartphones registered to a vehicular crowdsensing application, sending reports or alerts about specific events, such as roadblocks, incidents, road closure, etc. The main components are therefore human users i, reports or contributions j, and spatio-temporal windows k. As a representative application fitting our discussed system model, the real-world dataset Waze is considered as a case study for the experimental validation of the proposed methodology.

In the Waze dataset, events and reports provided by users are divided into spatio-temporal windows, whose definition is based on variations in time of the day and day of the week. Here, it is assumed that each day and time of the day defines a specific spatio-temporal window. Human users along with their sensing behaviour contribute data in the form of reports on the status of the traffic at different sensing regions by using smartphone-based PS applications [28, 17, 124]. Such sensing task may be either explicit (i.e., done directly by humans) or implicit via the sensors (e.g., sensors equipped to smartphones, wearables, vehicles) the humans own [17]. The contributions sensed by the humans are analysed and aggregated by the vehicular crowdsensing application to trigger and publish an event. This facilitates better decision making in the physical space.

The proposed modelling approach, and detailed in the next paragraphs, is described in Fig 7.9, where the first block shows the multi-layer social sensing platform from the IoP, where layers represent the various services and, at the same time, it is defined also the weighted multiplex social sensing among users, where weighted relationships are those among users and layers are the various channels of social interaction. The second block is the game-theoretic modelling where, starting from weighted social multiplex network, social interactions between users are explored and the evolutionary dynamics of human sensing behaviours are modelled. The emergence and sustainability of cooperation is quatified by varying the network topologies, homophily and multiplexity. Once detected the games and network topologies leading to the emergence and sustainability of cooperation, the QoI and the users' behavioural reputation scores in the network deriving from the analytical model are analytically defined and measured. Thus, based on these statistical estimators, the experimental validation on a real MCS application, Waze dataset, is conducted by defining and quantifying Quality of Contribution (QoC) and composite user reputation scores.

These measures allow defining the DSS and incentive mechanism design, measuring its performance.

7.3.1 System Model

Table 7.6 List of Symbols.

Symbol	Description
M	Number of layers.
N	Nodes' population.
S	Set of strategies.
P_i	Payoff of node i.
δ_{ij}	Homophily difference.
K	Selection intensity.
η_i	Scaling factor.
γ_i	Social honesty.
N_{Ci}	Number of cooperative behaviours.
N_r	Number of rounds.
N_{nb}	Number of neighbours.
QoI	QUality of Information.
R_i	Reputation Score.
QoC	Quality of Contribution.
τ_{ij}^k	Truthfulness of a contribution j at time k.
RS_i	Composite User Reputation score.
$Nagg(j)$	Aggregation of reports.
$RSagg(j)$	Aggregation of reputation score.
$U^+(z)$	Number of users with $RS_i > 0.5$.
C_j	Confidence.
I_i	Incentive.
B	Total budget allocated for incentives.
U	Total number of users.

Let us consider a multiplex network of M layers and N nodes, as defined in section 3.2 and in section 3.3. Each node is a human user with a different contribution profile and interacting with other users. Fig. 7.11 describes the multi-layer social sensing modelling approach. Layers represent various services exploited by the users, and the multi-layer interactions may affect users' sensing behaviour, and their choice to actively and qualitatively contribute (i.e., cooperate) to the sensing process. Thus, the proposed MCS multi-layer modelling approach is dual: since it is both an IoP-based weighted multiplex social network, in terms of weighted interactions between users, and a multi-layer social sensing platform, in

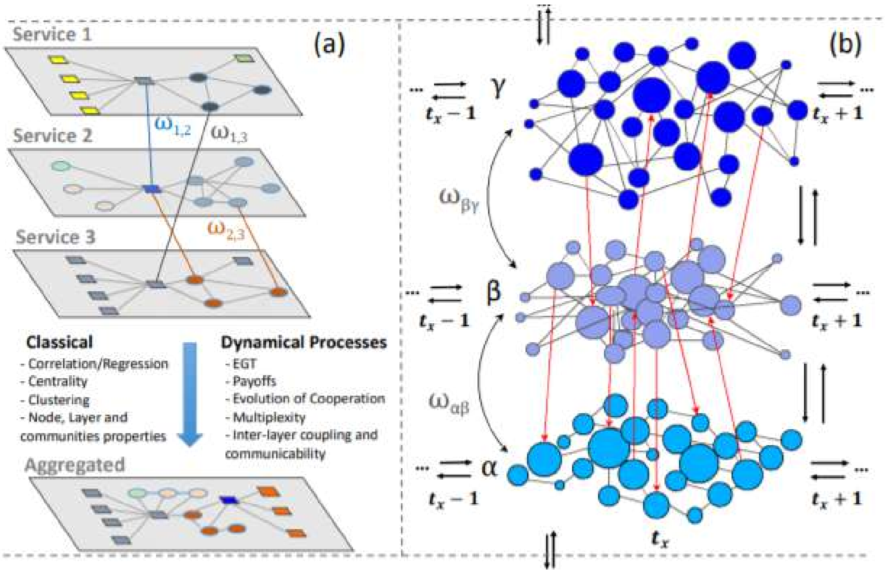


Fig. 7.10 Multi-layer Social Sensing and inter-layer coupling on a Weighted Multiplex Social Network. Reprinted from: [45].

terms of services (see Fig. 7.11). Indeed, users, while providing and sharing information on various services (see Fig. 7.11 (a)), interact on the social multiplex network changing their behaviour towards other users in the network and the whole MCS application (see 7.11 (b)), thus impacting on the reliability and operation of various services. The aggregated layer conveys all the structural information contained in the multi-layer social sensing. In Fig. 7.11 (b) we show the importance of considering the dynamic patterns of connectivity deriving from the coupling between layers of the social multiplex network. To characterise and measure such heterogeneity, the definition of weight for links between nodes at each layer is based on a combined measure of eigenvector-like centrality and homophily (see 3.3 and 4).

In order to quantify and capture the social dynamics of human users' behaviours on the social multiplex network, it is useful to resort of evolutionary game theoretic (EGT) approach. This allows us to obtain a multi-scale analysis of social dynamics and derive the impact of multiplexity on the users' sensing attitude in MCS applications. In particular, here, the focus is on exploring the evolution of cooperation, intended as the emergence and sustainability or resilience of cooperation on the multiplex network. For the analysis of human sensing cooperation through EGT, it is useful exploiting different social dilemmas, the iterated forms of the PD, the SD, the SH and the HG, with different characterisation, reflected by the specific payoff matrix representing its rules of interactions (as showed in section 4.2.4). Cooperating means honestly contributing and participating to the sensing task, such that human user decides to pay a cost of providing his contribution. In order to have a high operational

reliability in a crowdsensing application and have a robust Quality of Information (QoI), also the other player should contribute. However, there could be users who decide to defect, such as not paying any cost of contribution for accomplishing the task, or relying on the contributions of others in a selfish way. In this case, if also the other player decides to defect, the task will not be accomplished with a negative effect for both players.
To explore and quantify the evolutionary dynamics of human sensing behaviours on the social multiplex network, it is considered the iterated forms of the above-described pairwise social dilemmas where, at each round of the game, human users can change their strategies or behaviours, based on imitation dynamics of the fittest strategies. The evolutionary process is simulated in accordance with the standard Monte Carlo simulation procedure, composed of elementary steps so that at each round a player i changes its strategy S_i and adopts the strategy S_j from player j with a probability determined by the Fermi function [47]:

$$W(S_j \to S_i) = (\eta_i)\frac{1}{1+exp[\frac{(P_i-P_j)}{(\delta_{ij}K)}]} \tag{7.4}$$

Therefore, a player i adopts the strategy S_j of another player j in function of the payoff difference $P_i - P_j$, and according to δ_{ij} and η_i values. δ_{ij} is the homophily difference between two human users; if this value is small, player i is more likely to imitate the strategy of j at each round. K is the selection intensity and quantifies the uncertainty in the strategy adoption process and it is defined as in [47]. η_i is the scaling factor defined according to the communicability function between layers of the multiplex structure [47]. A complete list of symbols with its fair meaning is summarized in Table 7.6.

Statistical Measures for Designing Incentive Mechanisms - QoI and Behavioural User Reputation Score

In order to design a novel incentive mechanism, it is necessary defining some statistical estimators related to users' behaviour.

Definition 4. *Social honesty of node i.*

$$\gamma_i = \sum_i \frac{N_{Ci}}{N_r * N_{nb}} \tag{7.5}$$

where N_{Ci} is the number of cooperative behaviours of node i over the N_r rounds of the game. N_{nb} is the number of neighbours for each node i. Thus, γ_i quantifies the level of cooperativeness of each user in the network, considering its behaviour against neighbourhood and it allows us to classify the contributors in honest. Here, $\gamma_i \in [0,1]$ such that $\gamma_i = 0$ reflects *a lack of cooperativeness, while $\gamma_i = 1$ means that a human user has been fully cooperative with a proactive attitude towards its social community and neighbourhood.*

Definition 5. *Quality of Information (QoI). By averaging this measure over the population, the overall measure of QoI in the network structure is obtained, defined as follows:*

$$QoI = \gamma_i^{av} = \frac{1}{N}\sum_i \gamma_i \tag{7.6}$$

Definition 6. *Reputation Score. The aggregated measure of behavioural reputation score R_i for each user i is given by the ratio between the local measure of γ_i for each node averaged over the global attitude of users in the network, given by the QoI measure, so that it is defined as follows:*

$$R_i = \frac{\gamma_i}{\gamma^{av}} = \frac{\gamma_i}{QoI} \tag{7.7}$$

R_i quantifies and relates the importance of contribution given by the user as compared with the overall QoI in the network.

User Reputation Score in MCS scenario

The MCS in vehicular networks where the interactions between human users/vehicles equipped with sensors have been modelled as a vehicular crowdsensing game. Each node participates to the sensing task and chooses its strategy based on some constraints related to sensing costs/risks and gains derived from the accomplishment of the sensing task. As discussed earlier, both the quantity (degree of participation) and quality (accuracy of contributions) of the reported events are considered in this model. They represent the contributors' profiles and have been used as input data. Then, following the proposed game theoretic modelling approach, the behavioural user reputation scores for each human node in the different configurations of network structure and social dilemmas is showed in Fig 7.11. In the figure it is evident how in the SF case, behavioural user reputation scores assume high values, significantly higher than in the ER and SW cases. Indeed, in the ER and SW cases scores are mainly distributed in the range between 0 and 0.4. In addition, the ER network behaves worse than SW in terms of behavioural user reputation scores.

7.3.2 Experimental Validation

Based on the social game-theoretic model presented below, the definition of neighbours is extracted from Waze, assuming that neighbours are those users indirectly interacting in the same spatio-temporal window. Furthermore, in order to distinguish the quality of reports,

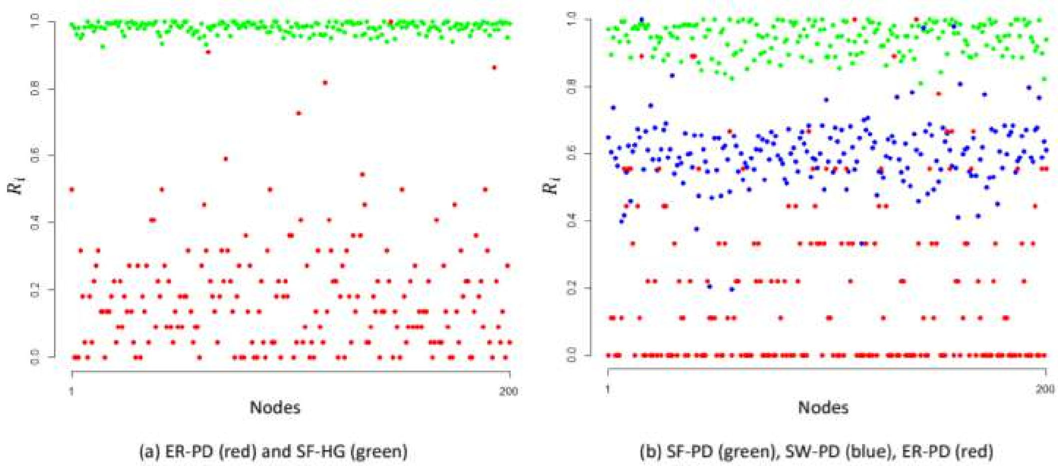


Fig. 7.11 Behavioural User Reputation scores. Reprinted from: [45].

and derive a measure of truthfulness of human user contribution, it is introduced the attribute Report Rating, assuming that a report is of high quality (cooperation) if Report Rating is strictly greater than the average measure of Report Rating.

Definition 7. *Quality of Contribution (QoC)*

The truthfulness τ_{ij}^k for any contribution j at time k, by modelling the problem as a weighted regression approach, where the predictor variables are: (i) the expectation from the opinion about a contribution and (ii) the spatial distance between the GPS-based location of the user i's smartphone and the cellular tower-based location. Truthfulness is a dependent variable deriving from these two terms. From our Waze dataset, the measure of the truthfulness of a report corresponds to the Report Rating. The truthfulness values τ_{ij}^k is mapped to a Quality of Contribution (QoC) value through the generalised linear models (GLM). Thus, by applying the regression through the logit function on τ_{ij}^k:

$$Q_{ij}^k = ln(\frac{\tau_{ij}^k}{1-\tau_{ij}^k}) \tag{7.8}$$

Q_{ij}^k is defined in the range $[-inf, inf]$ and it allows to determine whether the odds of the contribution j is true or false. The logit function is a monotonically decreasing function giving lower weights to $\tau_{ij}^k < 0,5$. In this model, it is extended the concept of QoC, which is related to the truthfulness of a contribution, by including a human user behavioural measure represented by the 'social honesty' γ_i of each use. It allows us to redefine the QoC as follows:

$$\bar{Q}_{ij}^k = \gamma ln(\frac{\tau_{ij}^k}{1-\tau_{ij}^k}) \tag{7.9}$$

where $\bar{Q}_{ij}^{k}$ is obtained by multiplying the previous QoC by the 'social honesty' γ_i of each user. By quantifying the degree of cooperation of user i in the previous rounds, it represents a measure of local 'reputation' of the user i, that amplifies his QoC. Indeed, in the measure of γ_i, it is included the number of cooperations, weighting this value based on the number of neighbours.

Thus, the evaluation is referred not only to the quality and to quantity of reports generated by user i over the time, but also to the local spatio-temporal distribution or density of cooperative reports over the overall number of reports at each window. This gives us a measure of spatio-temporal density of cooperation, and the importance of a contribution is inversely proportional to the density of cooperative reports: the lower is the density, the most critical is that spatio-temporal window, and the higher is the incentive to be assigned to that user. Moreover, γ entails a measure of persistence of cooperation, namely the number of times or spatio-temporal windows where a user contributes a high quality report (i.e., Report Rating strictly greater than the average of Report rating).

Definition 8. *Composite User Reputation Score RS_i. By including both the expected truthfulness τ_{ij}^{k}, and the newly defined measure of QoC derived also from users'degree of cooperation in the complex network. Aggregating the QoCs of the contributions generated by each users in the network, the composite user reputation score is the following:*

$$RS_i = \sum_{k=1}^{T} \bar{Q}_{ij}^{k} * p_{ij}^{k} \tag{7.10}$$

where p_{ij}^{k} is equal to 1 if the user i has generated a contribution (or report) j at time k, otherwise it is equal to 0.

Decision Support System (DSS) and Incentive Mechanism Design

Fig. 7.12 conceptually displays a map of the various aspects of the proposed methodology. Starting from the dynamic patterns of connectivity, the multi-layer social sensing framework, which includes homophily, network heterogeneity and multiplex structure measures, and the game-theoretic modelling guides choices according to human sensing behaviours. It leads to evaluate and quantify the human-centric policies, defining a MCS space that allows us to quantify the truthfulness measures for designing incentive mechanisms. From this, it is obtained a Decision Support System (DSS) able to perform a decision making process related to disbursing incentives to users based on dynamic and human-centric policies. These policies represent a minimised set of rules extracted from both qualitative and quantitative information and data related to human users and their behaviours. Thus, the DSS results from

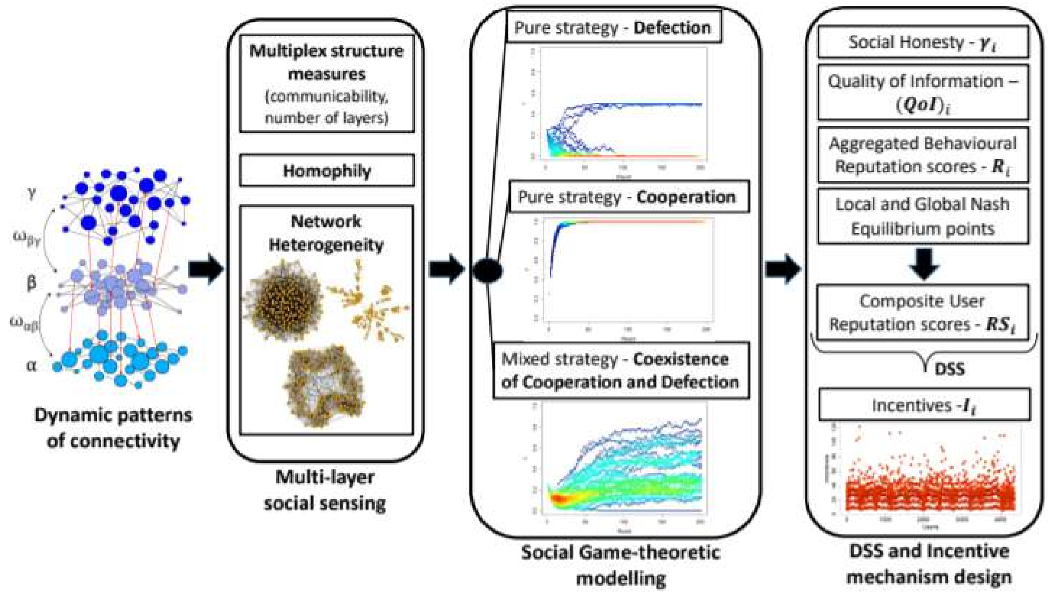


Fig. 7.12 Social game-theoretic modelling for designing incentive mechanisms in MCS. Reprinted from: [45].

the analysis and quantification through a social game-theoretic modelling approach which allows us to join and combine multiplexity, network heterogeneity and human-related factors represented by homophily. As described in the section 7.3.1 the system is able to distinguish honest from selfish and malicious users by computing their QoC and user reputation, where the defined measures of QoC and user reputation encompass the evolution of user behaviours in the network. Thus, both measures are inherently dynamic and derive from the evolutionary dynamics of user sensing behaviours in the network.

The DSS must be able to decide at runtime which event among multiple reported events is most likely to be accurate. Here, it is defined two-level DSS, based on a lightweight model. The first level is linked to decide what type of event to publish, that is evaluating the most likely event type that has occurred. This first decision level is required due to the presence of contributions or reports received simultaneously in the same sensing region but related to more than one event type. A confidence value for each reported event type j is computed based on the relative quantity and quality support for each event type j. The second level must determine whether to publish or drop an event. To this aim, there should exist sufficient evidence to suggest that the most likely event has actually occurred. Based on the extent of evidence, this decision level therefore allows us to discriminate if the publication of this event will result in a benefit or gain. This aspect aims to prevent orchestrated fake events, since honest reporters will not report anything in the absence of any event.

Based on the Waze dataset, it is assumed that among the reported events, the occurred event corresponds to the mostly reported event by only considering high-quality reports. Let the Waze application receive reports from different users in a common spatio-temporal window. Known the users' reputation score from the last spatio-temporal window $N_{agg}(j)$ is the aggregation of all these reports. $RS_{agg}(j)$ is the aggregate reputation score of all users reporting the event type j. $U^+(z)$ denotes the total number of users with a positive reputation score $(RS_i > 0,5)$.

Definition 9. *Confidence. The overall confidence on any event type j C_j using a weighted sum of quantity and quality supporting each event type j is defined as follows:*

$$C_j = \frac{N_{agg}(j)}{U^+(z)} + 1(1-\nu) * \frac{RS_{agg}(j)}{\sum_{i \in U^+(z) RS_{agg}(j)}} \tag{7.11}$$

Therefore, for j-th event, the first term represents the relative support for quantity, while the second term represents the quality. The weight $0 \leq \nu \leq 1$ *is the preference factor associated with the evidence types, and it is tuned based on available contextual spatio-temporal information of a given type of event or risk policy.*

Based on the above sections, the proposed incentive mechanism in mobile crowdsensing applications which is inherently dynamic and fair.

Definition 10. *Incentives received by user i.*

$$I_i = \frac{RS_i}{\sum_{m=1}^{U^+}} \frac{B * U^+}{U} \tag{7.12}$$

where B is the total budget allocated for incentives, and U is the total number of users or the population in the system. The ratio between the reputation score of user i and the reputation scores of all the other users showing a positive reputation score (on average behaving mostly as cooperators in the network) represents the relative reputation of the user i in the overall system. It acts as a discounting factor to the maximum possible incentive that any user in the network can gain. Users with higher relative reputation scores will end up getting higher rewards.

Incentivisation of Users

As explained before, the proposed model is based on an evolutionary game-theoretic approach including the concepts of homophily, network structural heterogeneity For this reason, in the definition user reputation scores and incentives, along with quality and quantity of contribution, the social honesty of users have been included. This has led us to provide a

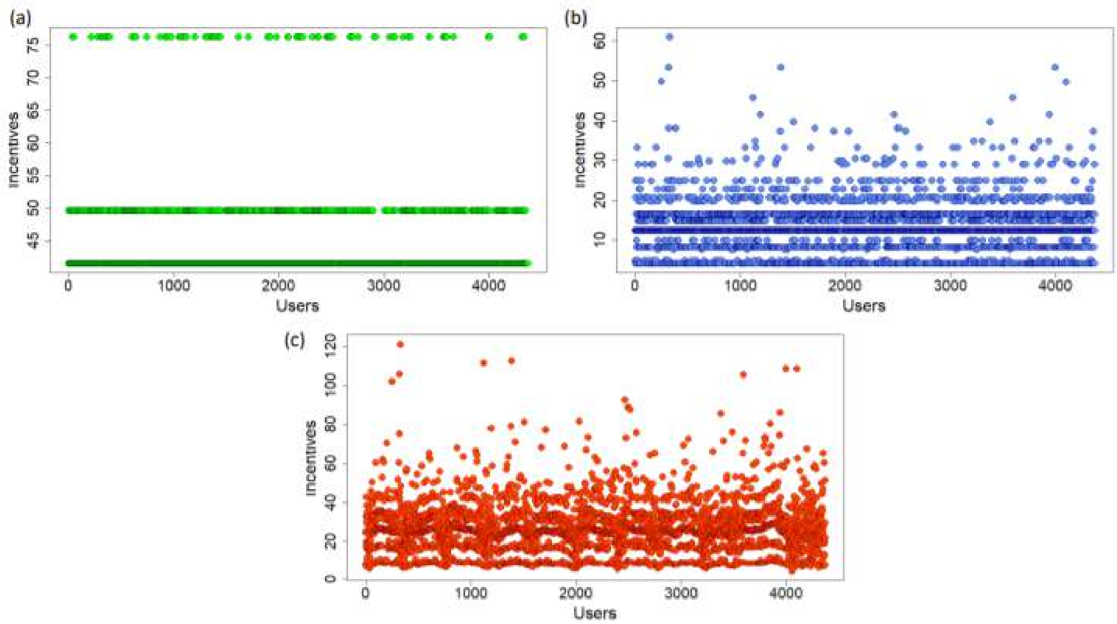


Fig. 7.13 Incentives disbursement. Reprinted from: [45]

novel definition of reputation scores and incentives that focus also on social dynamics and behavioural aspects derived from human cooperation. Indeed, this definition includes also the number of times a user cooperates in the various windows, or behavioural persistence, and the spatio-temporal distribution (or density) of cooperation in the different windows. Moreover, the introduction of these two novel aspects in the design of incentive mechanisms allow us to translate the idea of indirect reciprocity and detect the 'super-cooperative' users. These users cooperate in the most critical windows and the MCS application needs to incentivise them to preserve the operational reliability of service. The Fig. 7.13 shows the experimental results obtained in terms of disbursement of incentives considering the different incentive mechanisms. Specifically, following the incentive mechanism based on quality and quantity, but without including neither persistence nor the local spatio-temporal distribution of cooperators (see (a)), only three levels or classes of users' incentives can be distinguishable. By including the persistence, incentives are more differentiated (see (b)), and the classification and distinction of users' incentives is even more marked if it is also consider the local spatio-temporal distribution of cooperators (see (c)). The reason is that in (c), along with the quality and quantity of provided reports and a macroscopic measure of persistence of cooperation over time, it is included also local and microscopic aspects. This leads to a higher discrimination of users and a distribution expressing differences between users both at a cooperation and social scale, that is also considering the social groups user belong to. Thus, the proposed mechanism avoids not only incentives losses deriving from disbursing incentives to selfish or malicious users, but also those losses linked with a lack of a further discrimination of users which include social network and behavioural factors, such as persistence and the spatio-temporal distribution of cooperative behaviours.

7.4 Summary Remarks

The models proposed in this chapter have investigated a systematic methodology, resulting from a complex modelling approach. In the first, exploiting user-generated data from the social networks and communications technologies, the model proposes an understanding of the interplay between the collective attention dynamics and the two co-evolving spreading processes as awareness and epidemics, in two interdependent and heterogeneous weighted multiplex networks, under emergency situations in consequence of the occurrence of an extraordinary event as the ongoing COVID-19 pandemics. In the second, the proposed methodology includes the definition of the Decision Support System (DSS) and the design of a novel incentive mechanism, extracting rules and human-centric policies or metrics to disburse incentives to human users. In these models, humans are considered as social nodes that interact each other on a weighted social multiplex network, where each layer corresponds to a distinct type of relation among them and is weighted. Both models are also data-driven and model-driven, in fact starting from user generated data related to MCS services or social platforms, statistical measures have been estimated and novel measures have been defined. From a analytical perspective, the proposed model defines a class of models, that can be adapted and refined according to specific rules and metrics. Furthermore, by considering human-related factors, game-theoretic approach and epidemic models the proposed methodologies aim to develop innovative ICT services, even more efficient, resilient and adaptive. The statistical estimators and the social predictive markers derived from this methodology are crucial in order to define new incentive mechanisms, timely crisis response planning or DSS, making the entire system more robust and resilient, stimulating pro-social behaviours based on collective mechanisms, such as the emergence of cooperation or the awareness diffusion. The proposed methodologies, enclosing social dynamics, multiplexity and human-related issues, may provide new insights in the future design of socially-aware and human-centric systems.

Chapter 8

Cognitive MEC's organization for distributed and connected network intelligence

Overview: Today, on the wake of the evolution towards 6G, the complex joining of communication systems and socio-technical aspects of human interactions, together with the tendency to put the intelligence at the edge of the network are gaining interest. In this viewpoint, MEC is considered as a promising candidate to support the deployment of the 6G communication networks, which transforms IoT devices at the end of the network into intelligent hubs which become able to deliver highly personalized services directly from the edge of the network, providing the best possible performance in mobile networks. In this way, it is enabled the so-called networked and distributed edge intelligence, which is based on the cognitive and organizational aspects, the dynamical resources' management and on the adaptiveness of end devices. Major challenges arise from applications related to the smart healthcare and smart city contexts, which have stringent constraints in terms of QoS in order to provide immersive and context aware applications. In this chapter, it is proposed a modelling approach based on complex system to design a novel organizational aspect of mobile nodes acting as MECs in 6G scenarios, through the introduction of the multiplex social and temporal networks, which allows us to consider proximity contacts and social aspects and EGT which acts as a reinforcement learning for end devices. In particular, the last sections of the chapter are focused on the definition and addressing the microservices compliant load balancing (McLB) problem for end nodes, acting as MEC servers considering the impact of the use, re-use and chaining of Web of Things resources in IoT mashups. [3]

[3] The models, results and discussion presented in this chapter are shown and published in these contributions: [9–12]

8.1 Introduction

Driven by the increasing number of high-resource demanding mobile applications and the shift of the intelligence at the edge of the network, MEC is considered as a promising candidate to support the development of the next 6G of communication networks [126], [119]. Considering that the edges are often populated by hand-held or wearable mobile devices, it becomes pivotal the analysis of the social network dynamics of users' behaviours. In fact, human beings, their devices and consequently their behaviours act as active elements of the networks, constituting a sort of heterogeneous and aggregated things interacting in this complex socio-technical ecosystem, with a crucial role in the design of the networking functions [100].

To deal with these key issues it becomes crucial considering artificial intelligence enhanced end-devices acting as MECs and with the abilities of self-organization, self-adaptation and optimization of their interactions and functions. To have no impact on their costs, the idea is to have cheaper nodes, executing less sophisticated computations and taking advantage of the cooperation between other devices. This approach leads to a common and distributed intelligence for the entire network rather than of single nodes, enabling scalability, adaptability and resilience. Thanks to learning algorithms on edge devices, realized using reinforcement learning [73] and game theory [103], the nodes become able to adapt themselves to changes in the system, altering their behaviours and acting in cooperation with the collective aim at achieving an overall successful result for the system. Therefore, it is it is crucial to allow software to be 'liquid' and to 'flow' from one device to another, allowing the computation is relocated after the design time and not 'a priori'. A solution in this sense is represented by microservices [92] able to develop modular lightweight application components which can be individually deployed on-demand. Differently from monolithic software applications, whose modules cannot be executed independently and are unsuitable for distributed systems, microservices are cohesive, autonomic, replaceable, and deployable independent processes interacting with each other through standardised interfaces [34].

In this viewpoint, major challenges arise from smart cities and smart healthcare applications, which, due to the technological developments in the ICT, have been actively engaged in finding solutions for sophisticated and innovative services. For instance, in the field of automotive, whose applications [13, 39], essential part of the smart city mobility, are based on leveraging vehicular communication to collect the output of on-board city vehicle sensors, merging them with smart city sensors and people generated-data. The challenge is to bring the intelligence to the edge, shifting the processing and computing capabilities to the automotive IoT devices, and considering their connectivity, on having a change in paradigm of urban planning, treating it as a complex relational system. On the other hand, healthcare is

experiencing a rapid transformation from traditional approach to a distributed patient-centric one, but there is a lack of features which insert into the systems the capability of spotting collective behaviours, envisioning dynamics of communication networks, that represent a key aspect to learn on how properly monitor them. Thus, to do this and, at the same time, to collect data about their habits, social interactions, and health without obstructing their lives, smart devices should be wearable and wireless [85].
In addition to these aspects, in order to effectively address certain needs, and on the way towards 6G, the interest is shifting from IoT to the Web of Things (WoT) which aims at providing a more efficient resource discovery and access mechanisms. WoT effectively allows Things to become Web Things that are accessible via RESTful Web APIs [67]. More precisely, the idea of the WoT is to reuse and leverage widely popular Web protocols, standards and blueprints, to make data and services offered by objects accessible to Web developers, exposing their data and services as Web resources [**?**].
The WoT is intended to enable interoperability across IoT platforms and application domains, enabling the discovery of Things for interaction with other Things or applications. This type of Thing exposure facilitates the creation of mashups, where services/data from one or multiple Things are combined with virtual Web resources.
In order to plan new systems and applications, following the previous assumption, it is useful the introduction of an innovative approach based on complex networks and evolutionary dynamics which allows us to focus on aspects such as densification, heterogeneity and distributed and context-aware self-organizing decision makers [119]. The multiplex network representation can capture complexity of application scenarios, and its impact on the cognitive organizational aspect of the MECs, resulting on a cooperative dynamical behaviour to ensure quality of service (QoS) [26]. To this aim, the considered application scenarios will be represented, in this chapter, resorting on interdependent weighted or temporal multiplex networks [24], focusing on QoS performance metrics and objective cost functions.

8.2 Evolutionary Dynamics of MEC's Organization in a 6G scenario through EGT and Temporal Multiplex Social Network

In this section, it is explored how the temporal multiplex social network (see section 3.4) [72], [24] of nodes, which represent the aggregation of user and hand-held devices acting as MEC, can capture the real complexity of a relational system, as proposed and showed in Fig.8.1. The attention is focused on the proximity contacts among nodes, on the social related aspects of interaction, and on the exploiting of opportunistic contacts based on human mobility and proximity, for D2D [123] sharing of communications and computations resources [150]. Through Evolutionary Game Theory (EGT), aspects of learning and connections in a multi-tiered infrastructure for the cooperation in terms of collaborative offloading and reduction of the whole system's blocking probability are investigated.

8.2.1 EGT for MEC's cooperation

Data communication networks are evolving, following a common and global trend: services and data, initially available only at remote clouds, are becoming accessible to the edges of the network thanks to MEC [81], [103]. The main benefit of a system which employs MEC is the possibility to enable the typical G application which are delay-sensitive and context-aware [127],[97] reducing latency and providing high bandwidth and computing agility in the computation offloading process [156], [144]. MEC transforms nodes into intelligent hubs which become able to deliver highly personalized services directly from the edge of the network, providing the best possible performance in mobile networks. For this purpose, the analysis of cooperative dynamics conducts to task offloading schemes in a synergistic, self organized and smart way. Cooperative schemes among MEC nodes, in comparison with other sharing schemes such as random sharing, give better results in terms of delays, energy consumption, and blocking probability, achieving an efficient load balance and a better QoS [26]. EGT have already been used in synergy with MEC to shed light on aspects of learning, cooperation and connections and showing how EGT can enhance the usage of the networking edge resources [103], also applying collaborative offloading schemes: a busy device can count on the collaboration of nearby idle devices to facilitate the task execution [70]. Evolutionary games application allows to MECs with limited-rationality to select an initial strategy and apply it to a specific network, receiving a feedback (the payoff) from the environment. After playing a game through many rounds, it is expected that MECs' behaviours will be completely adjusted to the dynamically changing environment, learning which is the most profitable behaviour for the whole system.

8.2.2 Model

Taking into account the properties of temporal multiplex networks described in 3.4, to analyze the considered scenario we resort to a temporal multiplex network $D\mathscr{M}$ composed by $M = 2$ layers α and β, populated by aggregated nodes of users and their hand-held devices which act as MECs (see Fig.8.1). The layer α represents the social interactions among them and, for the sake of simplicity, we consider that, under the time window T of observation, this graph

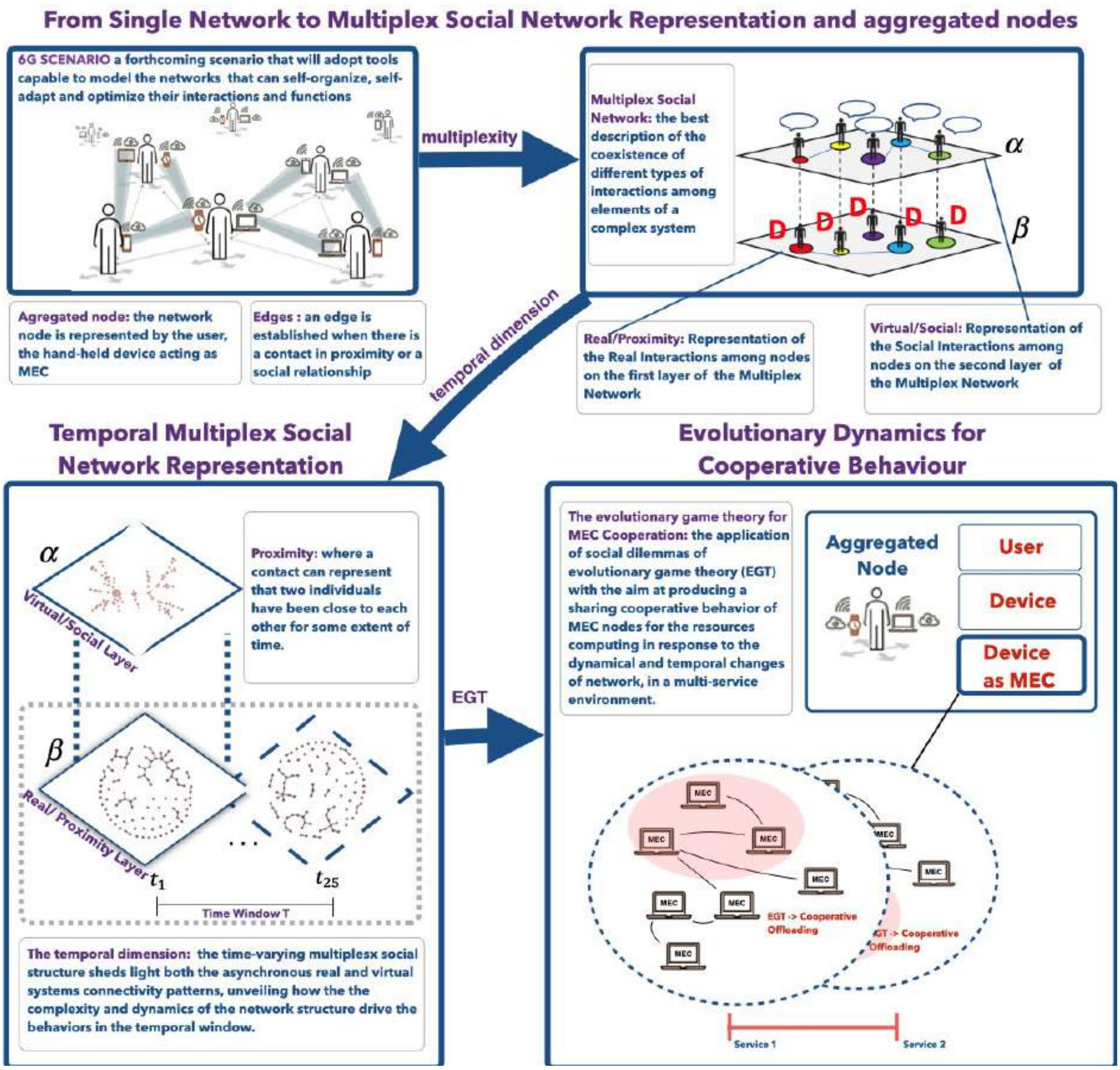


Fig. 8.1 Evolutionary dynamics for MECs' organization in 6G scenario through temporal multiplex. [11]

does not have time variation. In layer β we have a representation of the physical proximity interactions among nodes. We consider proximity more as a boolean condition, than as a precise measurement of distance.

In order to explore the evolution of cooperation among aggregated nodes acting as MECs in $D\mathscr{M}$ we introduce a game theoretic-approach. In particular, we consider the Prisoner's Dilemma Game (PD) (see section 4.2.4 for further details). The evolutionary dynamics of the PD have been simulated in accordance with the Monte Carlo procedure, considering elementary rounds of the game, in which players decide to change or maintain their strategy in accordance with the Fermi function:

$$W(S_x \rightarrow S_y) = \eta_x \frac{1}{1 + exp[\frac{P_x - P_y}{\delta_{xy} K}]} \tag{8.1}$$

A player x on the layer α decides to adopts the strategy S_y of node y playing on the layer β, taking into account the payoff difference $P_x - P_y$ between the payoff P_x acquired by the node x and the payoff P_y of the node y, calculated in accordance with the PD's payoff matrix (see section 4.2.4), the homophily measure δ_{xy} and a communicability measure η_x which evaluates the dependency between a player's strategy in a layer and its related players from other layers, quantifying the coupling between layers. K is a noise factor [48], [45]. Cooperation for nodes in $D\mathscr{M}$ means that two MECs exchange each other computation requests when one of them is overloaded. To quantify the role of the evolution of cooperation in the computing, it is introduced the definition of the blocking probability.

Definition 11. *Blocking Probability P^t_{Bi} of node i in the time step t. It is the probability to be in the state in which the incoming requests will be dropped as they cannot be stored at the data center of node i or forwarded to its neighbours:*

$$P^t_{Bi} = \frac{1}{k_i^{\overrightarrow{m}}} \sum_{j=1}^{N} \sum_{R^j_n = T_j}^{R^j_k} \pi_{R^i_k R^j_n} \cdot \pi_{R^*_j} \tag{8.2}$$

where $k_i^{\overrightarrow{m}}$ is the multidegree of node i [99]; R^j_n is the number of service's requests incoming to a neighbor j of node i; R_k is the maximum requests' number allowed, as k indicates the buffer size of nodes in $D\mathscr{M}$. T_j is a threshold equal to the number of requests which node j is able to accept. $\pi_{R^i_k R^j_n}$ is the probability to be in the state where i has a number of requests equal to its buffer size k and j has a number of requests equal to n; $\pi_{R^*_j}$ is the probability of the neighborhood of j to cooperate. In fact, the interplay between a given node and a neighbor is not only affected by their two strategies but, indirectly, also by that one of its *other neighbors, involving the dynamics of changing strategies, as expressed in Eq. 8.2.2 and the probability to cooperate.*

A complete list of symbols with its fair meaning is summarized in Table 8.1.

Table 8.1 List of Symbols.

Symbol	**Description**
$D\mathscr{M}$	Dynamical multiplex social network.
M	Number of layers.
S	Set of strategies.
P_x	Payoff gained by a node x.
δ_{ij}	Homophily difference.
η_x	Scaling factor.
K	Selection intensity.
$P^t_{B_i}$	Blocking probability of a node i in time step t .
$k_i^{\overrightarrow{m}}$	multidegree of i.
R^j_n	Number of services' request.
R_k	Maximum request number allowed.
k	Buffer size of i
T_j	Maximum number of requests acceptable by i.
$\pi_{R_{k^i}R_{n^j}}$	Probability to be in the state $R_{k^i}R_{n^j}$.
$\pi_{R_{k^*}}$	Probability of neighbourhood of i to cooperate.

8.2.3 Performance Evaluation

Simulation Setup

Simulations have been conducted considering the temporal multiplex network $D\mathscr{M}$ consisting of $M = 2$ layers and following the approach described in Section8.2.2 and shown in Fig.8.1. Both the layer in $D\mathscr{M}$ are composed by $N = 100$ nodes. The layer α is modelled considering the Scale-free network (SF) [16] as topology and the layer β simulating the dynamic proximity network through a STERGM simulation with random edge formation and dissolution effects. We have iterated the PD game for a number of elementary rounds equal to the number of time steps $t_i = t_1, \ldots, t_{25}$, within T, in which $D\mathscr{M}$ is observed. To build the model, do computation and obtain our results we used the programming language R and the IDE RStudio. The findings were generated thanks to the packages and ndtv, tsna, TERGM and igraph [116], [133].

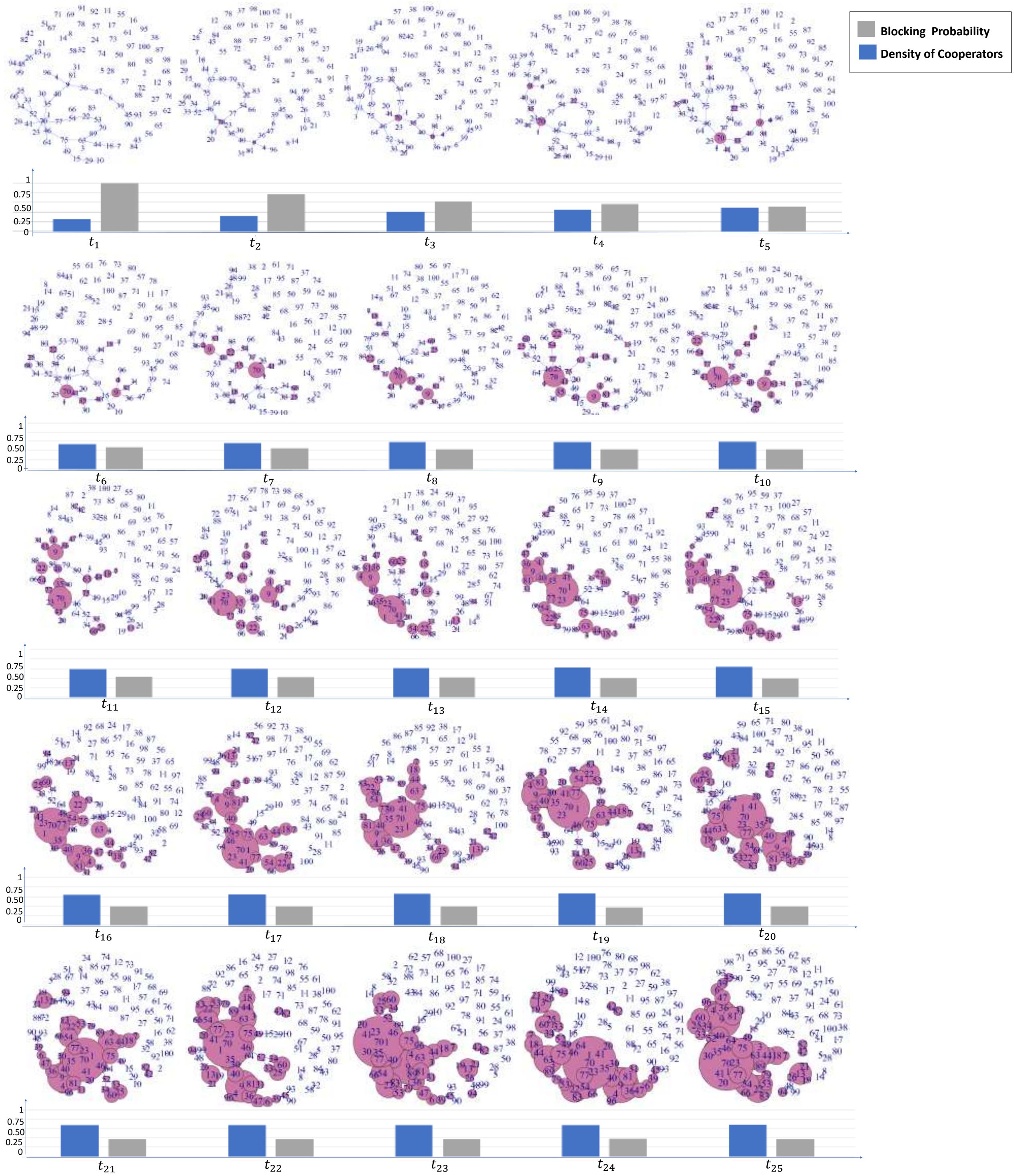


Fig. 8.2 Effects of evolutionary dynamics and time-varying topology on the blocking probability.

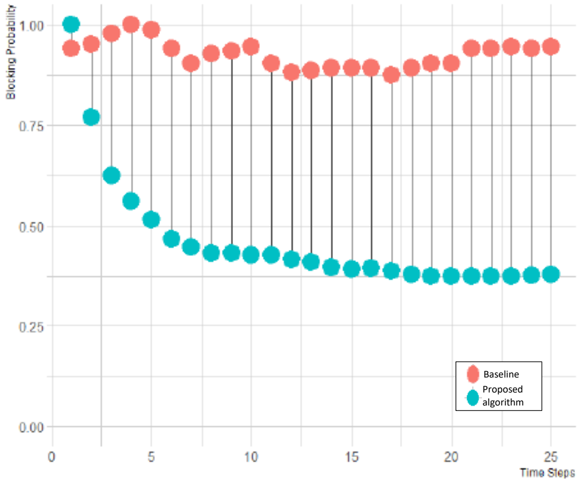


Fig. 8.3 Comparison of blocking probability Evolution.

Numerical Results

Taking into account all the simulations' conditions presented in Section 8.2.3, in the upper side of Fig.8.2 is is showed the timeline of layer β evolution which, for each t_i, represents the variation of potential impact of service load on MECs, but also the time-varying neighborhood with whom to cooperate to improve the capability to provide services. The introduction of the multiplex representation allows us take into account the influence not only by neighbors in β but also by nodes' counterparts in the layer α in nodes' behaviours. In each graph the nodes' size is proportional to its number of cooperations in t_i. At the bottom of the Fig.8.2 we display both the density of cooperating nodes (in grey) in the whole population and the global blocking probability P_b of the system (in blue) versus t_i; For the sake of simplicity, we assume that the flows of service requests arrives to MECs according to a Poisson distribution with rate of λ_i. The dynamics of nodes' cooperation co-evolves with the time-variation of the network structure and the application of the EGT leads to a general increasing of cooperators density, over the time steps t_i, despite of time-varying nature of interactions. EGT, acting as a learning algorithm, gives nodes the opportunity to tune their behaviour, in accordance with the environment and other players' choices, with the aim of reaching the common good for the system. The MECs benefit from their own cooperation which impacts on the global blocking probability P_b gaining higher capacity to provide services.
Furthermore, in Fig.8.3 starting from the same network hypothesis, it is computed the P_b evolution in the t_i time steps by comparing a baseline case with the proposed algorithm application. Since, in the baseline the EGT effect are excluded, in this case there is a constant maintenance of the P_b values during the time window T. Differently, by using the proposed

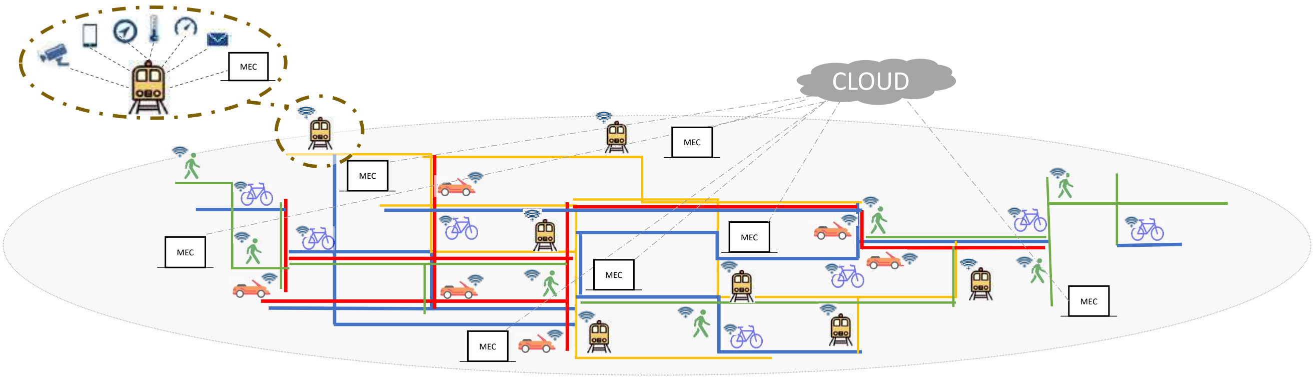


Fig. 8.4 Smart City Scenario.

algorithm the competition dynamics jointly with the multiplex structure impact on the P_b dynamic trend, lowering its mean value and decreasing its values in time.

8.2.4 Application Scenario: Smart City

In relation to a smart city scenario, as represented in the Fig. 8.4, an innovative approach can lead to shift the processing and computing capabilities to the automotive IoT devices, and considering their connectivity, on having a change in paradigm of urban planning, treating it as a complex relational system. This leads to a shift in perspective towards analytically exploring how the multiplex network representation can capture complexity in urban patterns, and its impact on the cognitive organizational aspect of the MECs, resulting on a cooperative dynamical behavior to ensure quality of service (QoS) [26].

Model

A theoretical approach to evaluate the interdependence of two complex network structures that create a dynamical and cognitive linkage between the changing layered urban scenario and the network of MEC nodes, both represented as weighted multiplex networks, is proposed in this section. This approach, as showed in Fig. 8.5, enable us to take into account the dynamics, the multiple interactions in a smart city scenario and the interplay among MEC nodes in a multi-service environment. To analyze this complex environment, we define two interdependent weighted multiplex networks, the first urban-based multiplex network $\mathscr{M}_1$ and the second MEC-based $\mathscr{M}_2$. We model each layer of both weighted multiplex networks

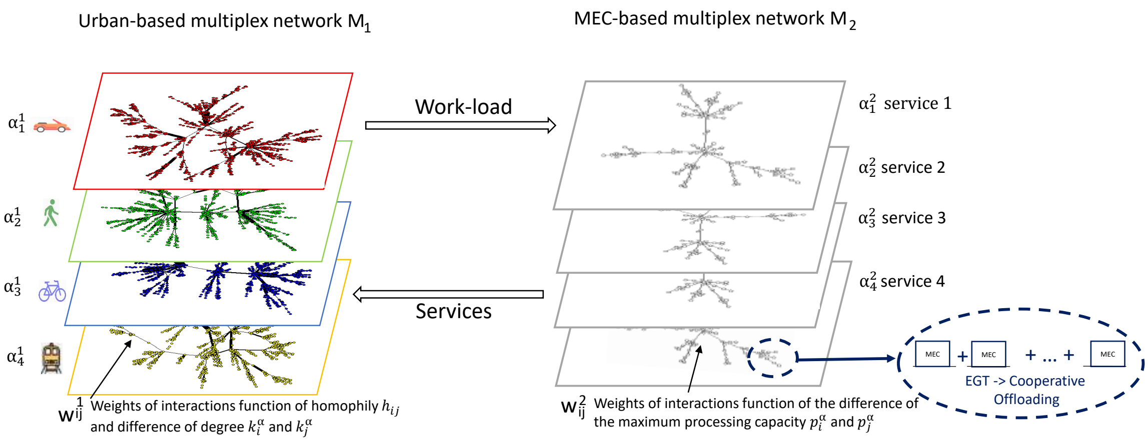


Fig. 8.5 Multiplex Modelling Interdependent Approach applied to Urban and MEC.

considering Scale-free network (SF) as topology [16].
The definition of multiplex network and its properties have been extensively listed and described in sections 3.2 and 3.3.

- **Urban-based multiplex network:** Taking into account the multiplex network properties above-mentioned, we consider a weighted multiplex network $\mathscr{M}_1$ where each of the L layer corresponds to a different road user, pedestrian, cyclists, trams, cars [104]. The links among nodes represent streets, or paths, and the nodes are the intersections among them. We assume that the city can be divided in several logical areas following the dynamical evolution of a city which reflects the science behind the urban morphology complexity [25], since it shapes in a hierarchy of different subcenters across many scale, structured around key factors from the city to neighborhoods. Referred to this weighted multiplex networks, we define the weights of the interactions in $\mathscr{M}_1$ as a measure of the heterogeneous mobility, and the homophily between nodes, as follows:

Definition 12. *Weights of interaction in* $\mathscr{M}_1$.

$$(w_{i,j}^{\alpha})^{\mathscr{M}_1} = h_{i,j}|k_i^{\alpha} - k_j^{\alpha}| \tag{8.3}$$

where k_i *and* k_j *are the degree of node* i *and node* j *respectively. Based on the homophily assumption presented in chapter 4, we define the* $h_{i,j}$ *as the tendency to have a path between nodes of the same logical area of the city.*

- **MEC-based multiplex network:** The weighted multiplex network $\mathscr{M}_2$ is populated by a set of MEC nodes, and each layer of this network is referred to a different service in which these nodes are involved. The links of $\mathscr{M}_2$ are weighted as follows:

  Definition 13. *Weights of interaction in $\mathscr{M}_2$.*

  $$(w_{i,j}^{\alpha})^{\mathscr{M}_2} = 1 + |p_i^{\alpha} - p_j^{\alpha}| \tag{8.4}$$

  where p is the maximum processing capacity that a node assigns to an application of the specific layer, based on requirements of services.

  We introduce a game-theoretic approach to explore the evolution of cooperation in $\mathscr{M}_2$ and how the number of cooperative nodes has a role in the service blocking probability [26]. We analyze different social dilemmas, the iterated forms of PD, SD, HG, SH (section 4.2.4). Cooperating means that two MEC nodes exchange each other generic computation requests, linked to a specific application, when one of them is temporary overloaded [26]. In fact, if a node i, at the edge of the multiplex network $\mathscr{M}_2$, decides to work on isolation, it can use a buffer, with size k to store computation requests when its CPU is busy. Consequently, it can have the possibility of dropping requests when this buffer is full. However, if multiple MEC nodes can come to rescue of each others, through cooperative behaviors of the node's neighborhood in the multiplex network $\mathscr{M}_2$, dropping probabilities will be reduced, exploiting both multiplexity and EGT. We also consider the Blocking probability as defined in Eq.8.2. For the sake of simplicity, in this case, only a time step is considered and not its temporal evolution.

A complete list of symbols with its fair meaning is summarized in Table 8.2.

Performance Evaluation

- **Simulation Setup** Simulations have been conducted considering the two weighted multiplex networks $\mathscr{M}_1$ and $\mathscr{M}_2$ both consisting of $M = 4$ layers. The $\mathscr{M}_1$ multiplex is composed by $N_1 = 1000$ nodes, and the $\mathscr{M}_2$ by $N_2 = 100$ nodes. To build the model, do computation and obtain our results we used the programming language R and the IDE RStudio. The plots were generated thanks to the packages Plotly and ggplot [116], [133], [128], [138].

- **Numerical Results** In the Fig. 8.6 is displayed the variation of multiplex participation coefficient P_i of nodes in the multiplex $\mathscr{M}_1$ in function of the Z-score of the overlapping degree of the nodes, shedding light on the number of edges and their distribution

Table 8.2 List of Symbols.

Symbol	**Description**
$\mathscr{M}_1$	Urban-based multiplex network.
$\mathscr{M}_2$	MEC-based multiplex network.
M	Number of layers.
N_1	Nodes population in $\mathscr{M}_1$
N_2	Nodes population in $\mathscr{M}_2$
$w_{i,j}^{\mathscr{M}_1}$	Weights of interaction in $\mathscr{M}_1$
$w_{i,j}^{\mathscr{M}_2}$	Weights of interaction in $\mathscr{M}_2$
h_{ij}	Homophily.
k_i^{α}	Degree.
p_i^{α}	Maximum processing capacity assigned at the layer α.
P_{Bi}	Blocking probability.

through the layers. This represents a sort of cartography which allows us to rank the nodes in terms of their role in the multiplex network [23], [24], as described in 3.3. Moreover, the size of each node indicates the variation of the strength distribution. We distinguish the case of high homophily between nodes i and j in $\mathscr{M}_1$ (black points) and low homophily (red points). The first case means that there is a high tendency to have links between nodes which belong to similar logical areas in which a city can be divided, differently from the second case in which the tendency is in having links between nodes of different logical areas. It is evident, in the red case, the presence of a few multiplex hubs with high strengths in conjunction with a multitude of regular multiplex nodes, showing a more heterogeneous hierarchical structure than the black case which in turns shows a homogeneous distribution of strengths. This means that, the second case is likely to create a highly homophilic connected clusters of nodes, disconnecting logical part of the city, decreasing the robustness. The introduction of the multiplex dimension of analysis allows also to classify the nodes and detect their roles in function of their structural properties and multiplex participation, resulting in a systematically understanding of the hidden urban patterns, within the considered scenario, [27] impacting on both the incoming workload for MEC nodes [140] and their cooperative dynamics in $\mathscr{M}_2$. In Fig.8.7 it is shown the global blocking probability P_{Bi} of MEC nodes in $\mathscr{M}_2$ in function of the number of cooperators and of the Participation Coefficient $P_i^{\mathscr{M}_2}$. We have simulated the evolutionary dynamics of different configurations of social dilemmas (HG, PD, SD, SH) for a number of rounds such that a dynamical steady-state is reached. Taking into account all these aspects, we are able to calculate the blocking probability P_{Bii} of the multiplex system depending

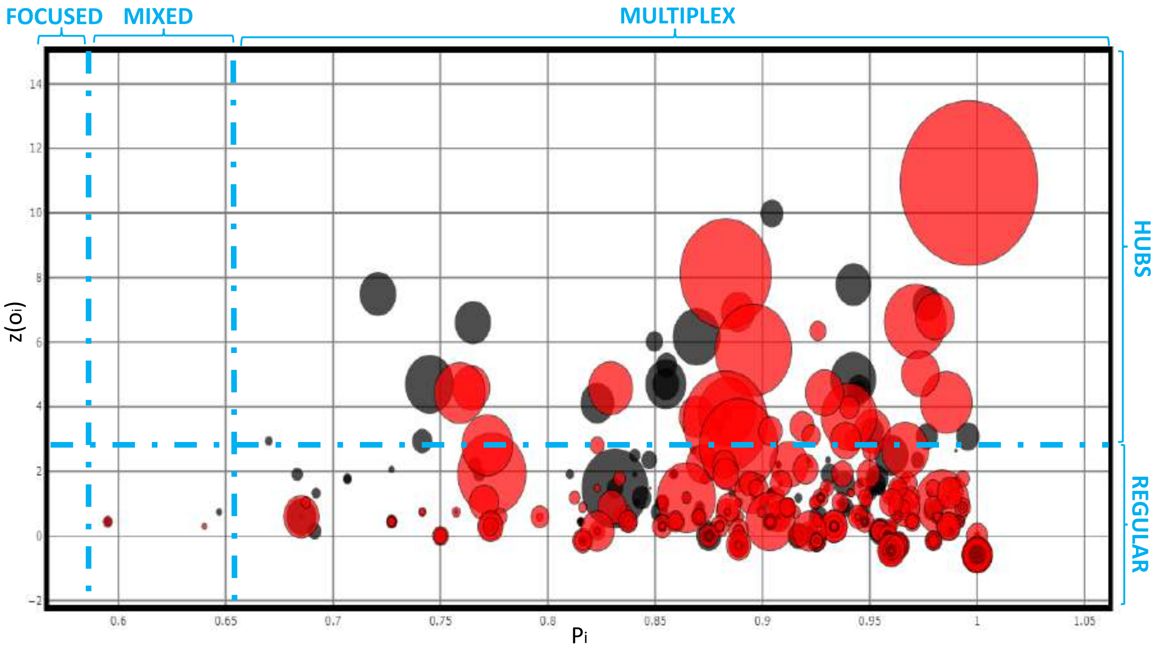


Fig. 8.6 Role of nodes in $\mathscr{M}_1$

on the role and each layer of interactions in which nodes are involved. Differently from the case of a single-layer representation, in which it is considered a service at a time, the introduction of the service-based multiplex dimension enables MEC nodes to gain from cooperation in several services and in the different layers. A node with high blocking probability in relation to a service can benefit from the cooperation of other nodes in all the layers, getting the opportunity to provide also other services. Therefore, nodes, in relation to their participation in the network, need different degree of cooperation from neighbors to offload the incoming load and reduce the Blocking Probability P_{Bii}. The dynamics of nodes' cooperation co-evolves with the participation of nodes in the network, which follows the environment service's requests. Thus, although the increasing of the Participation Coefficient $P_i^{\mathscr{M}_2}$ resulting on, from one hand into an efficient involvements in more services of the MEC multiplex nodes, and on the other hand in a increasing of blocking probability, the introduction of EGT dynamics leads to a decreasing of P_{Bii} regardless of the number of incoming service's requests, when dynamical steady-state is reached.

8.2.5 Application Scenario: Smart Healthcare

The assumed scenario is an innovative smart (Ambient Assisted Living) AAL that provides a multi-service environment towards patients, people with recognised frailty syndromes,

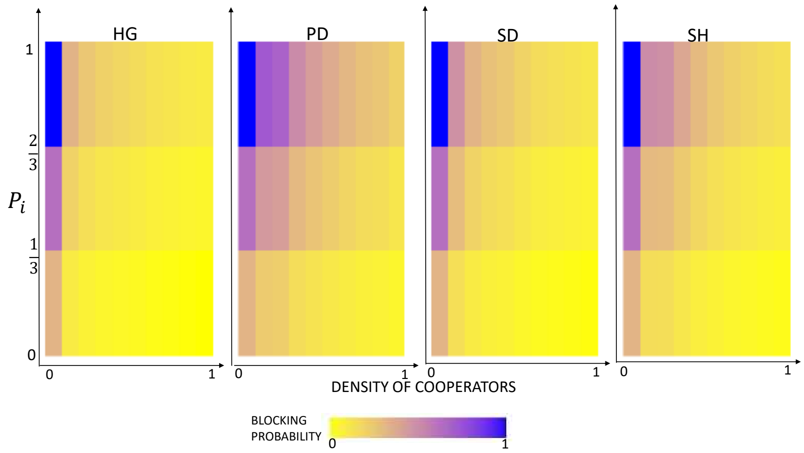


Fig. 8.7 Blocking probability of MEC nodes in $\mathscr{M}_2$ (Automotive IoT devices)

leveraging the advantages related to 6G technology, mobile edge computing, and complex networks algorithms. Data can be transmitted between devices, (such as medical devices, IoT, hand-held devices, etc.) in short range through D2D communication. In this assumed scenario, from one hand, patients are represented as social network nodes linked to each other through different ties (such as real and virtual). Moreover, from this network we can extract big data related on information diffusion, collective awareness, behavioral dynamics and service requests. From the other hand, we have MEC, which guarantees the providing of service in the multi-service environment.

Model

Considering that in AAL we can have different types of service requests, we represent the MEC as nodes of a multiplex network, layered as service-based. In this multiplex network formalization we analyze the fitness of statistical parameters which rules the cooperation of MEC nodes, to guarantee the service requirements. The first step of the proposed modeling procedure consists of defining a social weighted multiplex network. In the first multiplex, each layer corresponds to a different type of social interaction between users in the AAL (real and virtual layers). In the second multiplex, each layer corresponds to a different type of interaction among MEC nodes, based on service type, eMBB or uRLLC. The mathematical definition of weighted multiplex network togheter with its main properties and measures have been provided in 3.2 and 3.3.

Definition 14. *Weights of interaction in $\mathscr{M}_1$. The weights are defined as function of the discrepancy of patients awareness on its own health conditions and the homophily with other patients:*

$$(w_{ij}^{\alpha})^{\mathscr{M}_1} = h_{ij}|\Delta aw_{ij}| + 1 \tag{8.5}$$

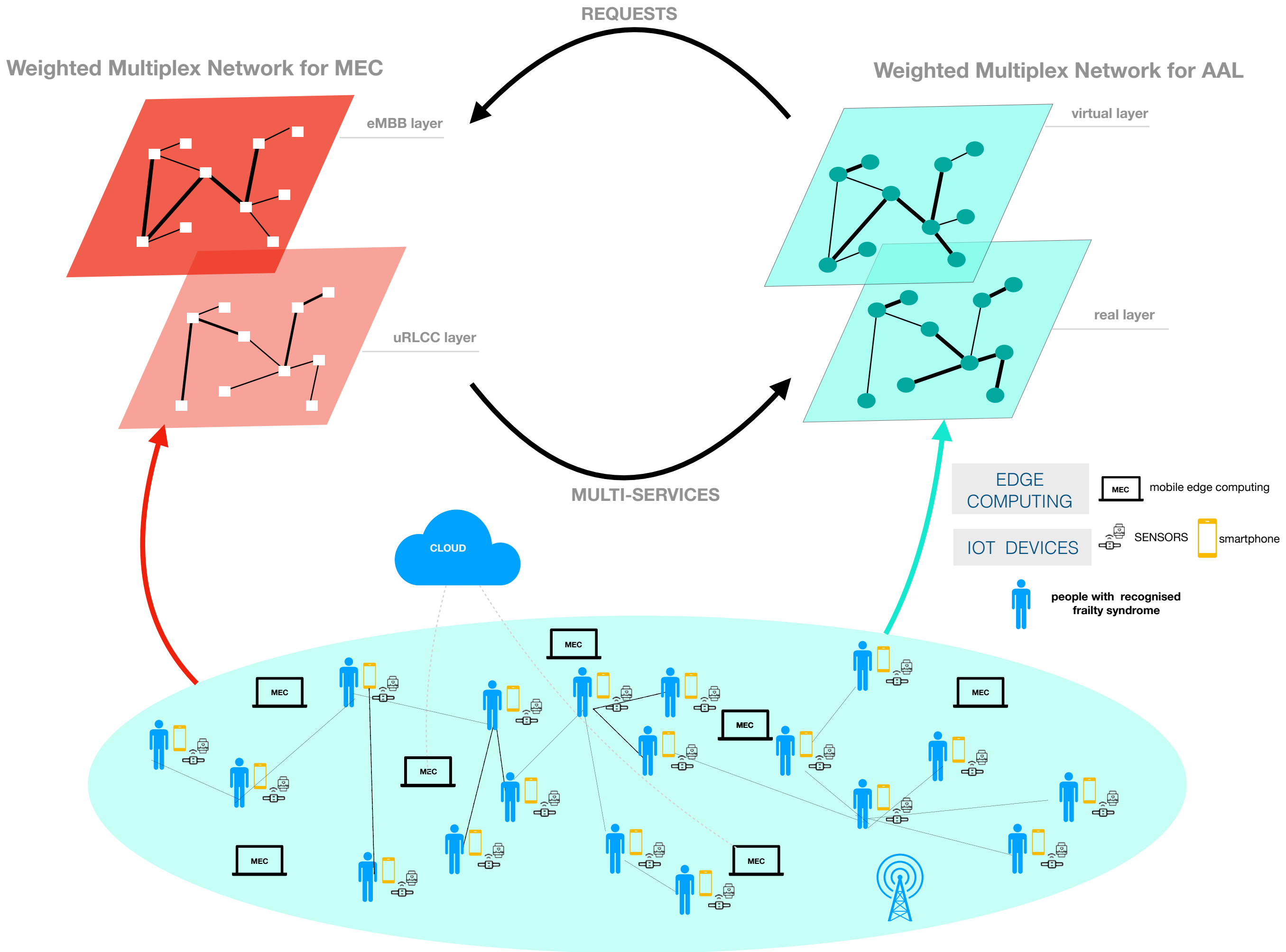


Fig. 8.8 Multiplex Network Representation of MEC in AAL scenario

Definition 15. *Weights of interaction in $\mathscr{M}_2$. In the multiplex $\mathscr{M}_2$, weights are function of p, that represents the maximum processing capacity that a node assigns to an application of the specific layer, based on services' requirements:*

$$(w_{ij}^{\alpha})^{\mathscr{M}_2} = 1 + |p_i^{\alpha} - p_j^{\alpha}| \tag{8.6}$$

Since the MEC resources are limited, one key challenge, in the proposed scenario, is offering the computing service in a multi-service environment with a low service blocking, in order to prevent inefficiency in the deployment of computing system in the proposed AAL scheme. For this purpose, here, the evolutionary game-theoretic approach is introduced, by enabling cooperation between MEC nodes in the multiplex network. Different social dilemmas are analysed: PD,HG,SH,SD (see section 4.2.4 for further details). In order to evaluate the performance of our proposed approach, we consider the blocking probability of the service as defined in Eq.8.2. A complete list of symbols with its fair meaning is summarized in Table **??**.

Table 8.3 List of Symbols.

Symbol	**Description**
$\mathscr{M}_1$	AAL-based multiplex network.
$\mathscr{M}_2$	MEC-based multiplex network.
Δaw_{ij}	Awareness discrepancy between node i and j.
$(w_{ij}^{\alpha})^{\mathscr{M}_2}$	Set of locations c_i considered
N_1	Population size in $\mathscr{M}_1$.
N_2	Population size in $\mathscr{M}_2$.
ρ	Density of cooperators.
P_{Bi}	Blocking Probability.

Performance Evaluation

- **Simulation Setup** Simulations have been conducted taking into account the two weighted multiplex networks $\mathscr{M}_1$ and of $\mathscr{M}_2$ both consisting of $M = 2$ layers. The $\mathscr{M}_1$ is referred to the multiplex representation of patients networks in AAL with $N_1 = 1000$ nodes, and the $\mathscr{M}_2$ is referred to the multiplex representation of MEC service-based network, with $N_2 = 100$ nodes. Each layer of both weighted multiplex networks is modeled by considering the SF network as network topology [16]. The reason behind this choice is due, from one hand, to its ability to give a boost to spreading collective dynamics [122] and, from the other hand, it represents the most suitable network topology for the emergence of cooperation [46][48]. In this way, it is possible

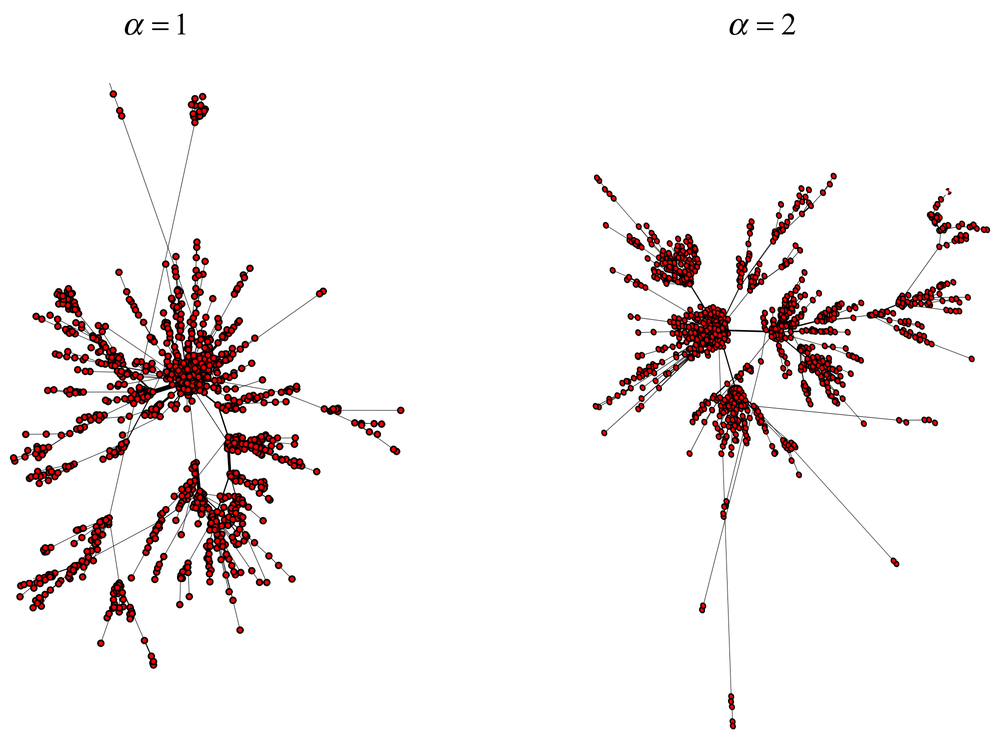


Fig. 8.9 Mobile Edge Computing Multiplex Network.

to investigate how such synthetic network, characterized by controlled topological properties, allow us to derive the potential gain both in terms of behavioral dynamics of the patients multiplex network and in terms of MEC cooperation to provide uRLLC and eMBB services. To build the model, do computation and obtain our results we used the programming language R and the IDE RStudio. The findings were illustrated thanks to the packages Plotly, ggplot and igraph [116], [133], [128], [138].

- **Numerical Results** Fig. 8.9 shows the $\mathscr{M}_1$ multiplex representation of patients networks in AAL. Notably, the choice of SF topology is induced by that SF is inherently heterogeneous, strictly resembling real-world networks displaying a skewed statistical distribution deriving from the preferential attachment rule [110]. Fig. 8.10 shows the aggregate network of the multiplex representation of MEC service-based network, underlining the multidegree. Fig. 8.11 displays the density plots to highlight the evolution of cooperation based on four different social dilemmas, respectively PD, SD, HG, SH in (a)-(b)-(c)-(d). The evolutionary dynamics have been simulated in all the different configurations of dilemmas for a number of rounds such that a dynamical steady-state was reached. Results confirm that SF is the most suitable network topology for the

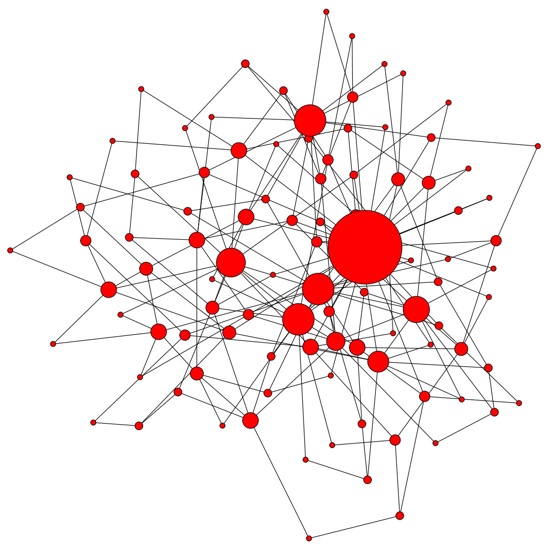


Fig. 8.10 Mobile Edge Computing Aggregate Network.

emergence and maintenance of the cooperation. Strikingly, HG, and secondly SD, achieve faster the highest density of cooperators than in the other cases, PD and SH, as expected from literature [90]. Fig. 8.12 sheds light on the impact of different social dilemmas (PD - SD - HG - SH (see respectively (a)-(b)-(c)-(d)) and multidegree values on the blocking probability of MEC nodes in the $\mathscr{M}_2$ weighted multiplex network. A node having a high blocking probability for one service gains in capacity from the cooperative behavior of its MEC nodes neighbours in multiplex to provide computing for the global multiservices environment. The evolution of cooperation in the weighted multiplex network of MEC nodes influence the probability that a service request is not executed by either the node or the cooperative neighbouring one, and it decreases as the number of cooperators increases. The multidegree of MEC nodes, displayed in Fig. 8.10, represents the potential impact of service load on the MEC nodes, but also the potential neighborhood with whom to cooperate in order to provide different services. Thus, it is able to trigger a cooperative mechanism. If a MEC node, in the weighted multiplex network $\mathscr{M}_2$, decides to work on isolation, which means that it maintains its interactions but without cooperative approach, potentially it could reduce its blocking probability by increasing the buffer size with a cost [26]. When there is not variation of buffer size, for that node, the higher is its multidegree the higher is its blocking probability, since in this case its neighbourhood, represented by the number of incident multilinks, is large and selfish thus it can increase its temporary load peaks. The gain

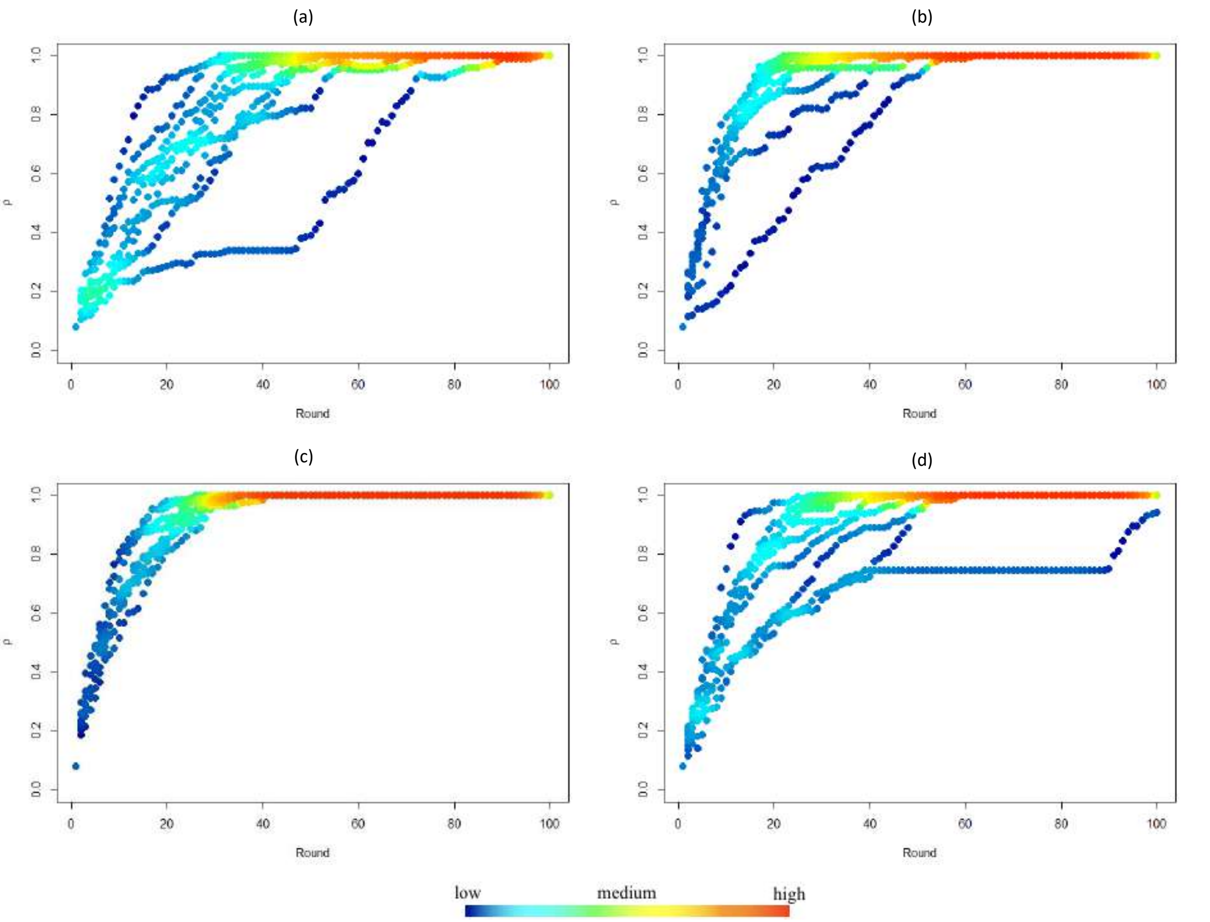


Fig. 8.11 The density of cooperation in various social dilemma, against the rounds of the game.

of the evolution of cooperation is more striking for the nodes with high multidegree measure as showed in Fig. 8.12. The evolution of cooperation in weighted multiplex networks, with scale-free structure as network topology of layers, is able to uniform the blocking probability regardless of the number of incident multilinks in a node, when dynamical steady-state is reached.

8.3 Cognitive Load Balancing Approach for 6G MEC Serving IoT Mashups.

In this section, we propose a solution to the Mircroservices Compliant Load Balancing (McLB) problem for IoT mashups in 6G by including the complex approach and paradigm jointly with the multiplex dimension representation and analysis of the networks. This

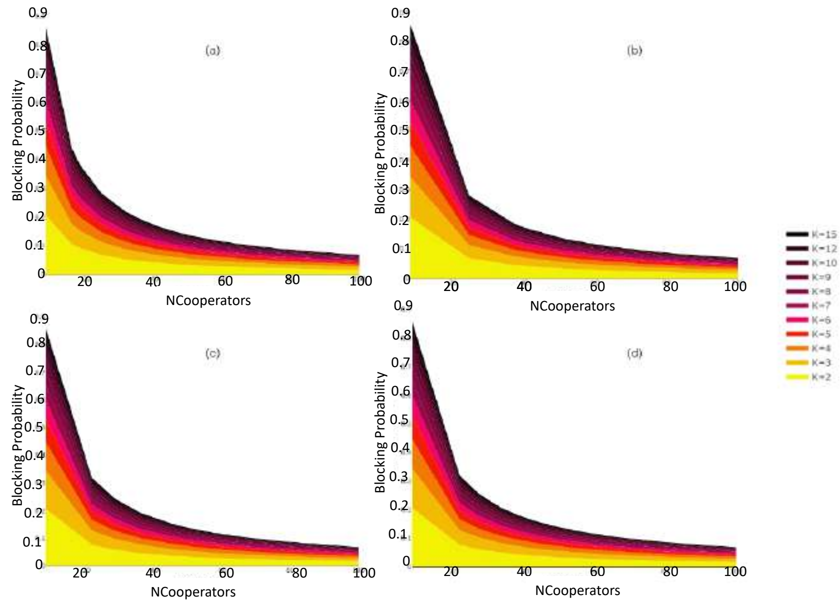


Fig. 8.12 The impact of Evolutionary Game Theory on Blocking Probability of MEC Nodes.

approach represents a change in perspective exploring how the multiplexity can capture the complexity in WoT mashups organizations and both the internal interdependencies, and their impact on the cognitive organizational aspect of the IoT devices, acting as MEC nodes. The aforementioned scenario is modelled through two interdependent and weighted multiplex networks [24, 30, 96] , the first one referred to the WoT mashups; the second one populated by the MEC servers whose computational load depends on the way in which the available Web resources are organized, used and, if possible, re-used in order to provide the final applications.
We quantify the impact that the knowledge extracted from the multiplex network representation has on engineering heuristics that guarantee load balancing and, consequently, quality of service (QoS), minimizing an objective cost function.

8.3.1 Modelling a Distributed MEC for WoT Mashups

Taking into account the definition, properties and measures of multiplex network described in section 3.2 and in section 3.3, the model proposed for the McLB problem consists of two interdependent weighted multiplex networks: $\mathscr{M}_1$, denoting a multiplex network that models the WoT section; and $\mathscr{M}_2$, denoting a multiplex network that models the MEC section. These networks are shown in Figure 8.13, and their role is clarified next.

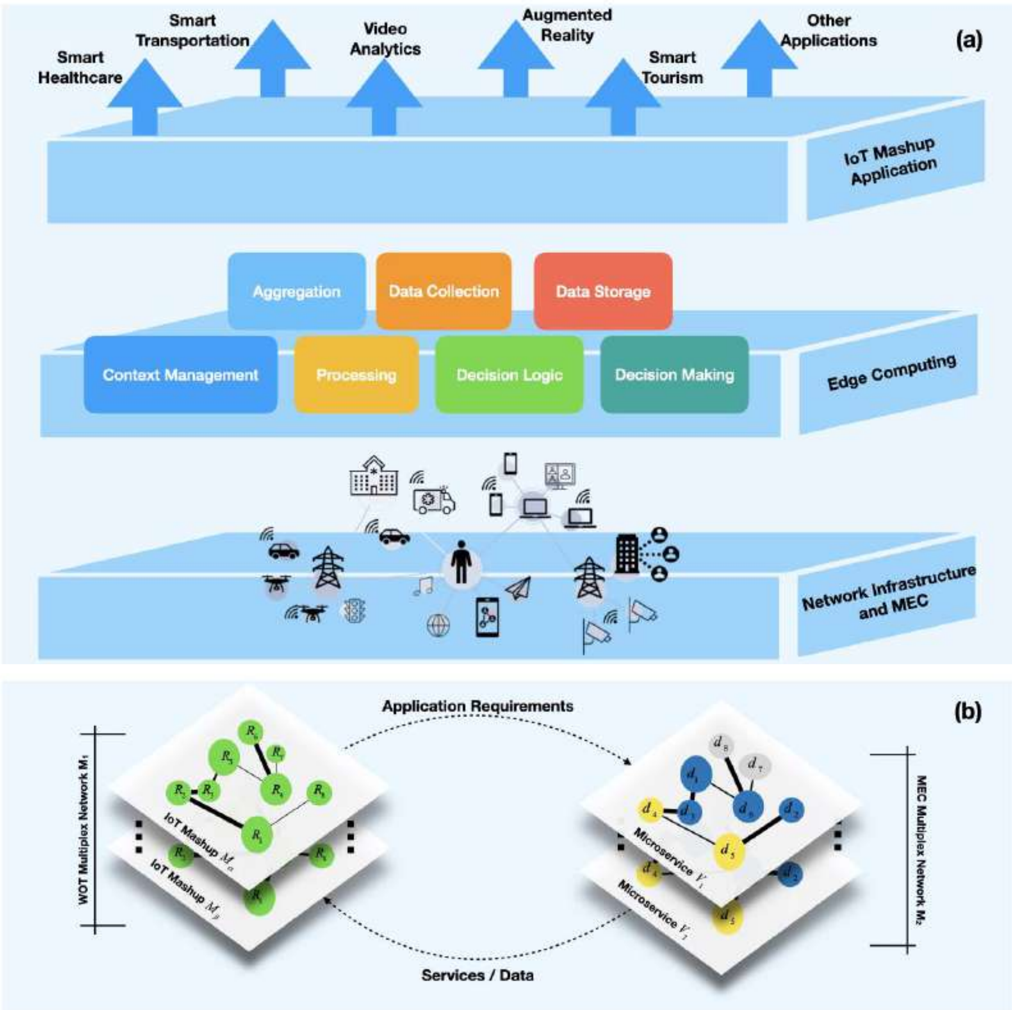


Fig. 8.13 Multiplex network interdependent model for the McLB problem.

Smart City Mashup Scenario

IoT cameras made available in a smart city can be used by visitors, to take video/photos, while acting alongside with other sensors (e.g., motion or smoke detectors) for security purposes or to ensure that safety regulations are followed. Other applications may include video analytics, location services, augmented reality, object recognition, etc. The devices will be shared by client applications building mashups, for use by locals or anyone around the world. Such mashups can integrate processing tasks to improve processes/services or to create new ones. MEC can create a powerful distributed computing environment that can be deployed to support low-latency services and IoT applications. Other scenarios, like industrial automation, smart homes, smart vehicles, among others, are also envisaged.

Basic Definition and Assumptions

The core idea of the WoT is that Things will be exposing services and data through RESTful APIs that other developers and devices can easily understand and use. REST is a resource-oriented architecture where every component of a system (sensor, sampling frequency, variable, etc) is called a resource, which can be individually addressed using a Uniform Resource Identifier (URI) standard scheme [67]. Resources can also enforce processing or decision tasks.

Definition 16 (Task)**.** *Resource implementing autonomous processing or decision logic on certain inputs and returning an output value. Besides simple logic, complex processing (eventually integrating other info; e.g., historical data) can be performed. The overall set of different tasks is denoted by $\mathscr{T}$.*

The exposure of Thing resources facilitates the creation of mashups. In general, a mashup is a way to compose a new service from existing services [40]. While this definition is focused mainly on information services, recent efforts on WoT standardization by W3C are allowing Thing resources to become part of mashups [64]. Recently, Rule resources have been introduced to implement observe-evaluate-actuate patterns, which are required in mashups.

Definition 17 (Rule Resource)**.** *Collection including a reference to a set of input resources, a task, and a set of output resources where task results should be placed. It is a REST-compliant mechanism to build observe-evaluate-actuate workflows. For a given rule $\mathscr{R}_i$, the set of inputs is denoted by $\mathscr{I}(\mathscr{R}_i)$, the set of outputs by $\mathscr{O}(\mathscr{R}_i)$, and task by $t(\mathscr{R}_i) \in \mathscr{T}$.*

Note that every element of the Rule collection (inputs, task, outputs) supports CRUD operations, which means that these can be modified on-the-fly (see [92] for more details).

The task feeds on the set of Rule input resources, and this set can change. Each input resource can also go through some format conversion or special treatment. The set of Rule output resources can also change on-the-fly, and notification templates are used for format adaptation. Rule inputs and outputs are Web resources, $\mathscr{I}(\mathscr{R}_i) \subseteq \mathscr{W}$ and $\mathscr{O}(\mathscr{R}_i) \subseteq \mathscr{W}$, where $\mathscr{W}$ denotes the overall set of Web resources, which means that Rule inputs, task and outputs can be hosted in different URIs and physical locations.

Definition 18 (Web Mashup)**.** *Workflow linking Web resources, which are identifiable digital, physical or abstract entities. A mashup $\mathscr{S}_i$ can be seen as a set of Rule resources and, therefore, can be denoted by $\mathscr{S}_i = \{\mathscr{R}_1, \mathscr{R}_2, ..., \mathscr{R}_{|\mathscr{S}_i|}\}$.*

Note that a Rule resource can be part of multiple mashups because there can be multiple Rule outputs, each with its own format, for participation in different workflows.

In future MEC network architectures there will be authorized third parties, like application developers and content providers, that will be able to use application servers integrated at the radio access network (RAN), what causes a multi-tenancy run-time and hosting environment for applications to emerge. Since MEC is a distributed cloud platform, breaking a monolithic application into loosely coupled microservices can bring significant gains in the performance, flexibility and robustness of IoT applications, as it is possible to relocate or replicate microservices. Microservices also have the advantage of being reusable across applications. Thus, an IoT related task can be implemented monolithically or it can be broken down into microservices (e.g, data processing, log file or database update, etc).

Definition 19 (Microservices)**.** *Independently deployable services communicating through a well-defined lightweight mechanism. A set of microservices serves a certain business goal/task. The available microservices is denoted by $\mathscr{V}$, and the set of microservices involved in task $t \in \mathscr{T}$ is denoted by $\mathscr{V}_t$.*

Definition 20 (Distributed MEC)**.** *Network solution providing services and computing functions required by clients at the edge. The set of application servers, or data centers, is denoted by $\mathscr{D}$. Each $d \in \mathscr{D}$ provides computing resources, storage capacity, connectivity and access to RAN information, and will be hosting microservices instances running as virtual appliances.*

In short, a microservices architecture can better ensure that applications are always on, due to replication, while a MEC infrastructure ensures a low end-to-end latency. This kind of architecture, together with the uncoupling of Rule collection components, provide the key elements for edge computing to work properly. Mashups can be built independently by the client, using a Rule-like mechanism, and processing/service tasks inside Rules can be moved to the MEC. Naturally, the MEC would benefit from load balancing across application servers, which would have to take into account interdependencies among microservices, i.e. the load on a successor microservice instance depends on the load from predecessor microservice instances [151].

Load balancing becomes the challenge that needs to be solved and aspects like MEC virtualization facilities and interdependencies among microservices have to considered. This problem is defined as follows.

Definition 21 (Microservices compliant Load Balancing (McLB) problem)**.** *Given a distributed MEC serving a set of client mashups, whose tasks involve one or more microservices instances hosted at MEC servers, plan for an adequate cooperative server MEC environment where load balancing is ensured.*

The multiplex network modelling is used to address this problem, as explained next.

Multiplex Network Modelling for McLB problem

The definition of multiplex network, together with its properties and measures have been extensively provided in sections 3.2 and 3.3. Taking into account the multiplex network properties, two interdependent weighted multiplex networks are proposed to model the McLB problem: M_1, denoting a multiplex network that models the WoT section; and M_2, denoting a multiplex network that models the MEC section. These networks are shown in Figure 8.13, and their role is clarified next.

- **WoT Multiplex Network**
  The multiplex network $\mathscr{M}_1$ is intended for WoT section modelling, where client mashups are built. Therefore, its nodes represent Rule resources exposed by Things, while its links/edges represent workflow wiring together such Rule resources. Rule resources can be part of multiple mashups, and $\mathscr{M}_1$ layers are the reflection of these structural interconnections.Thus, for a set of up and running mashups, the network graph at layer β, for $\mathscr{M}_1$, is denoted by $\mathscr{G}_\beta^{\text{WoT}} = (\mathscr{R}^{\text{WoT}}, \mathscr{E}_\beta^{\text{WoT}})$, where $\mathscr{R}^{\text{WoT}} = \cup_{\beta \in \{0,\ldots,L^{\text{WoT}}\}} \mathscr{S}_\beta$. The set $\mathscr{S}_\beta$ includes the Rule resources used by the mashup defined at layer β. Also, $\mathscr{G}_\beta^{\text{WoT}} \equiv \mathscr{G}_\alpha$, $L^{\text{WoT}} \equiv L$, $\mathscr{R}^{\text{WoT}} \equiv N$ and $\mathscr{E}_\beta^{\text{WoT}} \equiv \mathscr{E}_\alpha$.

  A Rule resource $\mathscr{R}_i$ is a Web resource of a particular type, available at some URI. As stated in Definition 18, the task performed by a Rule uses input Web resources, denoted by $\mathscr{I}(\mathscr{R}_i)$, and after performing some task the output is placed at one or more output URIs, $\mathscr{O}(\mathscr{R}_i)$, which will feed into other Rules. According to [92], the overall execution logic of the Rule resource is the following: *every time a Rule input is updated,*

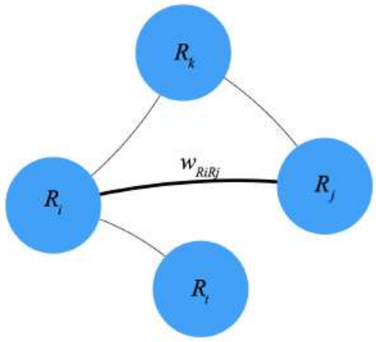


Fig. 8.14 Weights of interactions in $\mathscr{M}_1$.

the Rule task is executed and if its state changes from False to True then notifications are sent to the output resources. When abstracting ourselves from intermediate URIs, it is possible to state that $\mathscr{R}_i$ task execution is triggered by Rules that precede Rule $\mathscr{R}_i$ in workflow, within the same layer or in other layers, and this influence will be modelled as follows. For a weighted multiplex network $\mathscr{M}_1$, it is assumed that the relevance of a link is greater when its endpoints have greater difference in the number of inputs. The weights of $\mathscr{M}_1$ interactions will be the following:

Definition 22 (Interaction weights in $\mathscr{M}_1$)**.** *In a weighted multiplex network $\mathscr{M}_1$, the weight of a link between endpoints $\mathscr{R}_i$ and $\mathscr{R}_j$ in layer α, denoted by $w^{\alpha}_{\mathscr{R}_i,\mathscr{R}_j}$, is given by:*

$$(w^{\alpha}_{\mathscr{R}_i,\mathscr{R}_j})^{\mathscr{M}_1} = 1 + |(k^{\alpha}_{\mathscr{R}_i} - 1) - (k^{\alpha}_{\mathscr{R}_j} - 1)| \tag{8.7}$$

where $k^{\alpha}_{\mathscr{R}_i}$ and $k^{\alpha}_{\mathscr{R}_j}$ are the degrees of $\mathscr{R}_i$ and $\mathscr{R}_j$ nodes in layer α, respectively.

The degree of a node is the number of interactions in layer α. Figure 8.14 illustrates such intra-layer interaction weights. This property is useful to shape interactions among nodes in a layer, allowing re-usability and chaining of resources to be improved. In addition, Rule resources interact with their counterparts in other layers. This is so because Rule resource are not only chained for the creation of a specific mashup, but also contribute to the formation of other mashups. This is captured by the interdependent layers of multiplex network $\mathscr{M}_2$.

- **MEC Multiplex Network**
  The multiplex network $\mathscr{M}_2$ is intended for MEC section modelling, where application servers or data centers are placed. While the network is populated by the set of application servers/data centers (network nodes), the layers refer to the microservices. In

each layer, an $n \in N$ will be hosting microservices instances running as virtual appliances. Multiplex representations allow us to establish relationships and to shed light on complex interdependence between microservices with respect to load distribution, reusability, computing capacity of hosting nodes and time involved. Therefore, links between nodes in $\mathscr{M}_2$ will have weights defined as follows.

Definition 23 (Interaction weights in $\mathscr{M}_2$.)**.** *Referring to the weighted multiplex network $\mathscr{M}_2$, the weight of link w_{ij}^{α} is given by:*

$$(w_{ij}^{\alpha})^{\mathscr{M}_2} = 1 + |f_i^{\alpha} - f_j^{\alpha}| \tag{8.8}$$

where f_i^{α} and f_j^{α} represent the computing capability of data centers i and j, respectively, that is dedicated to microservice α. This accounts for multiple microservice instances.

- **WoT and MEC Interplay**
By assuming that WoT applications can share Rules, when building their worksflows, and that Rule tasks can be decomposed into small and light components/microservices, it becomes possible to distribute microservices across servers. This leads to complex interactions between MEC servers and, given the chains of resource requirements involved, multiple levels of abstractions with complex interactions can emerge. To capture the connection between Rule resources in $\mathscr{M}_1$ and microservices distributed across servers populating $\mathscr{M}_2$, the complex load for each node i in $\mathscr{M}_2$ is defined. This represents the computation overhead due to the involvement of MEC nodes in the multiplex network representation. The complex measure $(b_i)^{\mathscr{M}_2}$ is defined as follows:

Definition 24 (Complex involvement of server i in $\mathscr{M}_2$.)**.**

$$(b_i)^{\mathscr{M}_2} = (P_i)^{\mathscr{M}_2} \times \sum_{\alpha=1}^{M_2} (s_i^{\alpha})^{\mathscr{M}_2} \times \frac{\sum_{\beta=1}^{M_1} \sum_{\{j \in N_1\}} (s_j^{\beta})^{\mathscr{M}_1}}{\sum_{\{j \in N_1\}} (P_j)^{\mathscr{M}_1}} \tag{8.9}$$

where M_1 and M_2 denote the number of layers in $\mathscr{M}_1$ and $\mathscr{M}_2$, respectively, while N_1 denotes the set of nodes in $\mathscr{M}_1$.

Note that $(P_i)^{\mathscr{M}_2}$ in expression (8.9) is the multiplex participation coefficient of a node $i \in N_2$, set of nodes in $\mathscr{M}_2$, measuring the involvement of MEC servers' resources in different microservices/layers. The higher the participation coefficient, the higher the computation load at the server, due to the fact that the node actively participate in multiple microservices. The $\sum_{\alpha=1}^{M_2}(s_i^{\alpha})^{\mathscr{M}_2}$ is the sum of the strengths of node i, calculated for each layer $\alpha \in \{1,...,M_2\}$. This measure depends on the importance of links, which has to do with the computing capacity difference of its nodes. The last component of expression (8.9) is the Reuse function for Rule resources in $\mathscr{M}_1$, where $\sum_{\beta=1}^{M_1}\sum_{\{j\in N_1\}}(s_j^{\beta})^{\mathscr{M}_1}$, summing the strengths of nodes in $\mathscr{M}_1$ over all layers $\beta \in \{1,...,M_1\}$, takes into account the heterogeneity of links as a consequence of $\mathscr{M}_1$'s weights (see Section 8.3.1). A greater strength implies greater heterogeneity at Rule resource inputs and consequently, additional loading for MEC servers in $\mathscr{M}_2$. The $(P_j)^{\mathscr{M}_1}$ is the multiplex participation coefficient of node $j \in N_1$, from the WoT-based multiplex network $\mathscr{M}_1$, and it represents a measure of how Rule resources in $\mathscr{M}_1$ are reused and chained in different mashups. The greater the multiplex participation coefficient, the more Rules are involved in different mashups, with no additional computation required on MEC servers. The $(b_i)^{\mathscr{M}_2}$ ends up measuring the commitment of MEC node i and, therefore, the probability of opting for local computation or offloading to neighbouring nodes. Thanks to this complex measure, an estimation is made regarding the probability that a node in $\mathscr{M}_2$ will compute locally or not.

- **Impact on Energy and Time** To measure the impact on both energy and time associated with computing that is held locally and offloaded, a cost function must be defined. As specified in Definition 19, each task $t \in \mathscr{T}$ can be served by a set of microservices $\mathscr{V}_t$ and, for the sake of simplicity, it is assumed here that such data load is initially distributed across microservices and MEC nodes (layers and nodes in $\mathscr{M}_2$, respectively) using a hypothetical distribution that depends on the degree k_i^{α}.

  Let $x_{it} \in \{0,1\}$ denote the offloading decision for node i regarding the task $t \in \mathscr{T}$. That is, $x_{it} = 0$ if the MEC server goes for the local computation, and $x_{it} = 1$ in case of offloading. According to such decision, the energy and time cost is defined as follows.

  Definition 25 (Decision Impact on Energy and Time)**.** *The total cost associated with decisions stored in matrix $\mathbf{X}_{N_1\times|\mathscr{T}|}$ is defined by:*

$$Cost(\mathbf{X}) = \sum_{i=1}^{N_1}\sum_{t=1}^{|\mathscr{T}|}(E_{it} + H_{it}) \tag{8.10}$$

where E_{it} is the required energy and H_{it} the execution time for task t initially allocated at node i. As operations will be performed locally or offloaded:

$$E_{it} = (1 - x_{it})E_{it}^{loc} + x_{it} \times E_{it}^{off} \tag{8.11}$$

$$H_{it} = (1 - x_{it})H_{it}^{loc} + x_{it} \times H_{it}^{off} \tag{8.12}$$

whose components are defined as follows [51]:

$$H_{it}^{loc} = \frac{c_{it} \times l_{it}}{f_i}, \tag{8.13}$$

where c_{it} is the number of CPU cycles, l_{it} is the task load and f_i is the computation capacity of node i in $\mathscr{M}_2$,

$$H_{it}^{off} = \frac{l_{it}}{r_i} + \frac{c_j \times l_{jt}}{f_j} \tag{8.14}$$

where f_j refers to the computation capacity of node j in $\mathscr{M}_2$, to which the task load is offloaded, and $r_i = B \times \ln(1 + \frac{p_i}{\omega_0 B})$ is the uplink rate for bandwidth P_{Bi}, p_i is the transmission power, ω_0 the channel noise,

$$E_{it}^{loc} = v_i \times l_{i,t} \times c_{i,t} \tag{8.15}$$

with v_i energy per CPU cycle and, finally,

$$E_{it}^{off} = p_i \times H_{it}^{off}. \tag{8.16}$$

A complete list of symbols with its fair meaning is summarized in Table 8.4.

Performance Evaluation

- **Simulation Setup**
  Simulations have been conducted considering a multiplex network $\mathscr{M}_1$ with $M_1 = 3$ layers, each layer representing an IoT mashup, that models three distinct kinds of weighted interactions and connectivity among the $N_1 = 1000$ nodes (Rule resources). A variable population for $\mathscr{M}_2$, $50 \leq N_2 \leq 500$ nodes (MEC servers), and a variable number for M_2 (microservices layers), $3 \leq M_2 \leq 9$, are assumed. Each layer of both weighted multiplex networks has a Scale-Free (SF) network topology [16]. SF networks are highly heterogeneous networks, characterised by a power-law degree distribution, with high degree correlation between nodes and degree distribution having a long

Table 8.4 List of Symbols.

Symbol	**Description**
$\mathscr{M}_1$	WoT-based multiplex network.
$\mathscr{M}_2$	MEC-based multiplex network.
N_1	Number of nodes in $\mathscr{M}_1$.
N_2	Number of nodes in $\mathscr{M}_2$.
M_1	Number of layers in $\mathscr{M}_1$.
M_2	Number of layers in $\mathscr{M}_2$.
$\mathscr{T}$	set of tasks.
$\mathscr{R}_i$	Rule Resource
$\mathscr{W}$	Set of Web Resources.
$\mathscr{V}$	Available microservices.
$\mathscr{V}_t$	Microservice involved in a task t.
D	Set of distributed MEC.
$w^{\alpha}_{\mathscr{R}_i,\mathscr{R}_j}$	Weights of interaction in $\mathscr{M}_1$.
$k^{\alpha}_{\mathscr{R}_i}$	Degree.
f^{α}_i	computing capability.
$w^{\alpha}_{h_i,h_j}\|_{\mathscr{M}_2}$	Weights of interactions in $\mathscr{M}_2$
$b_i^{\mathscr{M}_2}$	Complex involvement.
$P_i^{\mathscr{M}_2}$	Multiplex participation coefficient.
$s_i^{\alpha M_2}$	Strength.
X	Cost decision matrix.
$E_{i,j}$	Required energy.
$H_{i,j}$	Required Execution time.
$E^{loc}_{i,j}$	Required energy in case of local computation.
$H^{loc}_{i,j}$	Required Execution time in case of local computation.
$E^{off}_{i,j}$	Required energy in case of offloading.
$H^{off}_{i,j}$	Required Execution time in case of offloading.
p_{h_i,h_j}	Relative frequency to use both hashtags h_i, h_j.
c_{it}	CPU Cycles.
l_{it}	Task load.
r_i	Uplink rate.
p_i	Transmission power.
v_i	Energy per CPU.
ω_0	Channel noise.

tail. SF networks fit many real-world networks and are characterized by preferential attachment and growth: *new nodes are added to the existing ones with a probability of attachment that is proportional to the degree of older nodes in the network.* Regarding

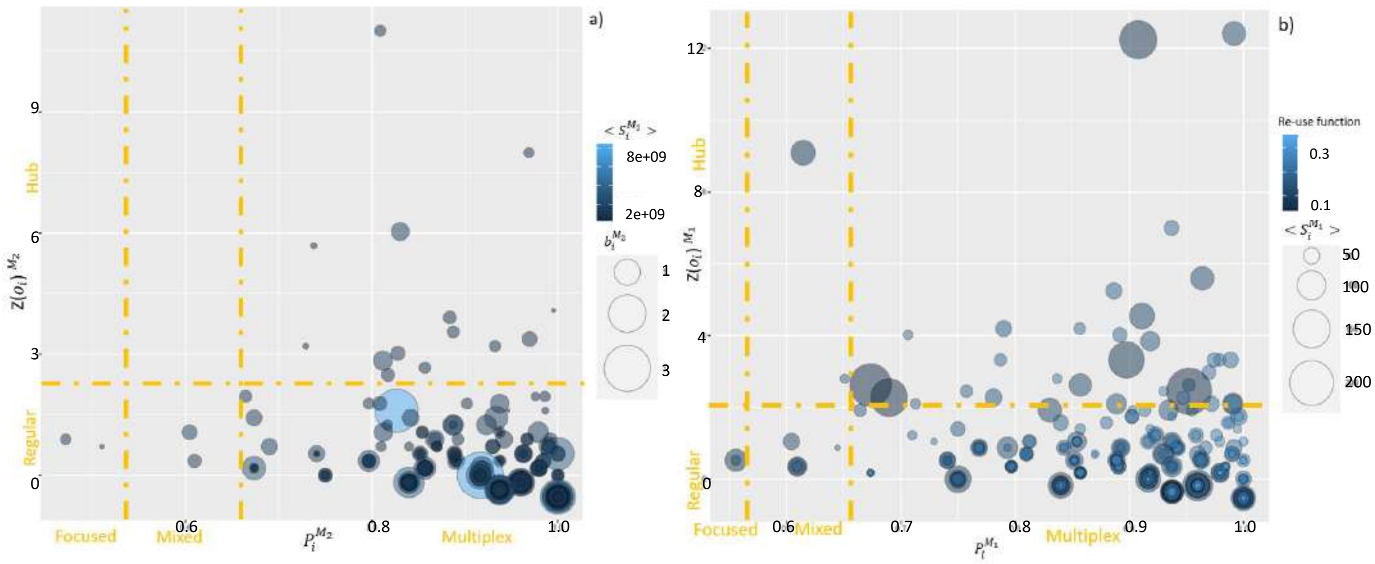


Fig. 8.15 Role of nodes in $\mathscr{M}_2$ (a) and in $\mathscr{M}_1$ (b).

to the remaining simulation parameters, it is assumed that the size/load of tasks is in the range $[0,20]$, i.e. $l_{it} \in [0,20]$ MB, and that tasks are spread across nodes following the hypothetical distribution described in Section 8.3.1. The energy consumption per CPU cycle is set to $v_i = (0.20 \times 10^{(11)})$ Joules per cycle. For the number of CPU cycles it is considered that there will be $c_{it} = 500$ cycles per bit. In order to take into account the heterogeneous computing capability of servers, a random computing capability $f_i \in \{0.5, 0.6, ..., 1\}$ GHz is used. The device's transmission power, channel bandwidth and background noise are $p_i = 0.1$ W, $P_{Bi} = 20$ MHz and $\omega_0 = -100$ dBm, respectively [51].

To build the model, perform computation and obtain results, the programming language R and IDE RStudio is used. Figures were generated using Plotly and ggplot packages [138], [128], [116]. Simulations ran on a personal computer with Intel(R) Core(TM) i7-8750H CPU, 8 GB RAM capacity and 2.20GHz frequency.

- **Numerical Results**

  Figure 8.15a) shows a cartography of the node roles in the multiplex network $\mathscr{M}_2$, plotting for each node i the multiplex participation coefficient $(P_i)^{\mathscr{M}_2}$ versus the Z-score $(z(o_i))^{\mathscr{M}_2}$ of the total overlapping degree. Since the overlapping degree of a node represents its overall importance in terms of number of incident edges, while the multiplex participation coefficient gives information about the distribution of incident edges across the layers, this cartography allows us to classify nodes merely in terms of their structural role in the multiplex network (see [24],[23]).

  In general, representing nodes as points in the $P_i - z(o_i)$ plane allows to identify three classes of nodes: i) focused, comprising the nodes for which $0 \leq P_i \leq \frac{1}{3}$; ii) mixed, comprising nodes having $\frac{1}{3} \leq P_i \leq \frac{2}{3}$; iii) multiplex nodes, comprising nodes with

$P_i > \frac{2}{3}$. Regarding the Z-score of their overlapping degree, it is possible to distinguish: *i*) hubs, for which $z(o_i) \geq 2$; *ii*) regular nodes, for which $z(o_i) < 2$. Moreover, through the colour of each node it is possible to show the variation of the mean strength distribution $\langle s_i \rangle^{\mathscr{M}_2}$ and through its size it is shown the complex involvement $(b_i)^{\mathscr{M}_2}$.

A finding from such cartography is that greater values of complex involvement $(b_i)^{\mathscr{M}_2}$ can be noticed in nodes classified as regular multiplex, confirming that the multiplex network representation is quite suitable to capture the complexity of the considered scenario, where computation is shifted to the edge. These nodes are regular because they have a low number of incident edges and multiplex as their links are well distributed across the layers (microservices in which they are involved). This means these nodes are involved in many microservices but their computation is not crucial for any of them. Furthermore, we can deepen the analysis, evaluating not only the number of nodes' incident links and their distribution across the layers but also the distribution of their average strengths. The strength is a function of weights (see Equation 3.3 for definition of strength) and according to Definition 23 it depends on the difference of computing capabilities among linked MEC nodes. A poor heterogeneity in the mean strengths' distribution $\langle s_i \rangle^{\mathscr{M}_2}$, as evidenced from the Figure 8.15a), is consistent with the scenario in consideration in which the nodes at the edges, that carry out the computation, have limited and not too different computation capabilities.

The complex involvement $(b_i)^{\mathscr{M}_2}$ represents the interplay between the two multiplex networks $\mathscr{M}_1$ and $\mathscr{M}_2$ (see Section 8.3.1) and strictly depends on the way in which the resources are organized and reused in the Wot-based $\mathscr{M}_1$, represented through the Reuse function. For this reason, Figure 8.15b) shows the cartography in the plane $P_i - z(o_i)$ for the nodes in $\mathscr{M}_1$. This time, the size represents the distribution of the average strength $\langle s_i \rangle^{\mathscr{M}_1}$, while the colour is the variation of the Reuse function. This cartography sheds light on how the multiplex network analysis results in a deepen understanding of the hidden organization of Web resources, their use and re-use in IoT mashups, which impacts on the computational load of MEC nodes in $\mathscr{M}_2$. In this case, considering an SF as network topology, it is possible to see that the most used and re-used Web resources are those classified as multiplex regular nodes. These Web resources participate in several IoT mashups but do not present a high number of incidents links in any of them. The nodes with lower values of Re-use function are the most critical nodes in term of computation because are characterized by high values of both $(P_i)^{\mathscr{M}_1}$ and $(z(o_i))^{\mathscr{M}_1}$ (multiplex hubs). This means that they are involved in many IoT mashups and, at the same time, in some of them they are important in terms of number of incident links. In addition, those with high average strength are even more

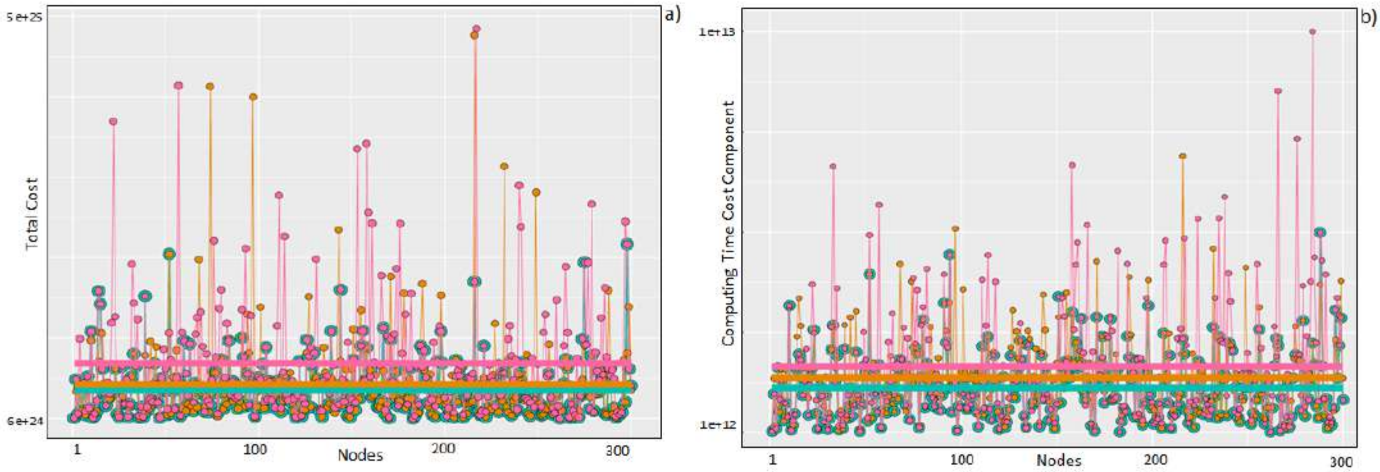


Fig. 8.16 Cost versus nodes: a) Total cost; b) Computing time component. Punctual and mean values are shown for three cases: local computation (in pink), offloading to neighbours (in orange), and cognitive computing decision (in green).

critical because they introduce further heterogeneity in computation (see Definition 22). Figure 8.16a) shows the cost for the case of $N_2| = 300$ nodes and $M_2 = 3$ layers. Points in the graph represent the cost (energy and time) associated with nodes for the following three cases: *i*) nodes always choose for local computation (orange points in the plot); *ii*) nodes always decide for offloading (pink points in the plot); *iii*) decision about computation is made in accordance to the values of complex involvement $(b_i)^{\mathscr{M}_2}$ (referred as the cognitive case; green points in the plot). In order to provide a heuristic (not optimal solution) to the McLB problem, in a distributed and collective way, the mean values of costs related to the three cases are shown. From such information it is possible to state that the cognitive case represents the most profitable approach, for the whole system, presenting the lowest mean cost.
Figure 8.16b) indicates the trend of the computing time, and it is clear that in terms of time the complex involvement choice is also quite convenient. This approach can be particularly suited to those distributed and mobile network contexts, whose services require priority and are extremely sensitive to delay.

The heatmap in Figure 8.17 displays a comparison of the total cost for the local, offloading or cognitive computation cases. Different population sizes are used for the multiplex network $\mathscr{M}_2$, N_2 ranging from 50 to 500 nodes. The number of layers, M_2, also varies and $M_2 = 3$, $M_2 = 5$, $M_2 = 7$ and $M_2 = 9$ cases are considered. The figure shows that the case where computation decision is taken according to the knowledge extracted from the multiplex network representation, through the measure $(b_i)^{\mathscr{M}_2}$, the

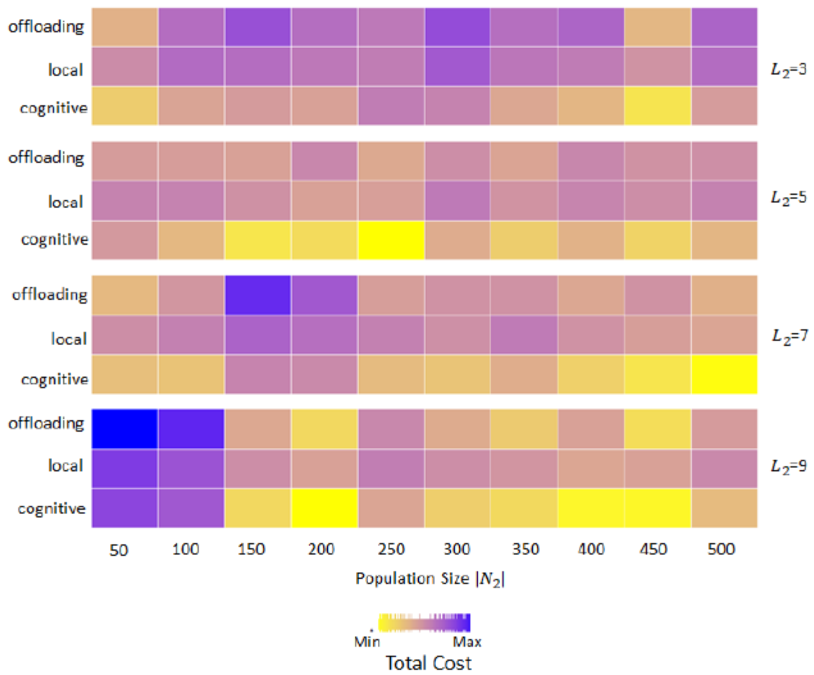


Fig. 8.17 Sensitivity heat map for the total cost when varying the population size and number of layers in $\mathscr{M}_1$.

cognitive case, presents the most profitable values for the whole system. Furthermore, as the population and the number of layers grow, this approach becomes increasingly convenient. In particular, for $M_2 = 9$ it is possible to see that a high number of layers means that the MEC nodes in $\mathscr{M}_2$ are involved in a large number of microservices, resulting in a major computation load and cost. Increasing the population, in the cognitive case, provides more capacity for self-organization, increasing the probability to go for the most profitable choice in terms of cost.

8.4 Summary Remarks

In this chapter innovative approaches have been introduced. This approaches are based on multiplex networks, proximity networks and EGT. The novelty consists in the introduction of key features able to fully describe and capture the complexity of 6G ecosystems. These ecosystems involve IoT, IoP or WoT platforms related to dynamically changing contexts as smart cities or smart healthcare. Heterogeneous resources and the computation capabilities of devices devoted to the computation must be used optimally in order to construct the connected and distributed intelligence of the network aimed at providing end applications, respecting their QoS, through the introduction of novel algorithms for dynamic managing of lightweight applications, as microservices.

The results shown and discussed in this chapter put in evidence that the multiplex representation provides and extra dimension of analysis but also an additional source of knowledge, enabling cognitive and distributed decision mechanisms, which have an impact on the QoS of final applications.

Chapter 9

Conclusions

In this chapter the research questions posed in the first chapter will be revisited, summarising the main results, contributions and the underlying key aspects addressed and presented in this Ph.D. dissertation.

9.1 Research Contributions and Questions Revisited

The main research contributions presented in this dissertation can be summarized answering the research questions posed in section 1.2:

- **What are the most suited tools and methodology to quantify the impact that micro-scale structures and dynamic properties have on macro-scale performance? In what terms is it possible to represent a 6G network as a complex system?**
  In Chapter 2 we have described the main features and challenges of the next 6G communication networks and the need for new approaches to study, model and design such networks. In the future 6G new and complex topics becomes even more central as emergent behaviours, evolutionary and collective dynamics, complex interactions and interdependence which have an impact on the macroscopic performances of 6G systems. To study all these aspects we have to rescue on a interdisciplinary and bio-inspired approach based on complex network theory, as discussed in chapter 2, and the mathematical frameworks of multiplex network theory, EGT and epidemic spreading modelling, reviewed, respectively, in chapters 3, 4, 5.

- **What is the most appropriate approach to measure, evaluate and characterize services and components in 6G networks?**
  In Chapter 6, we have described a node profiling process that step-by-step allows defining different aspects extracted from a complex networks analysis, to shape a

profile which embeds macroscopic, microscopic, mesoscopic, dynamical and learning properties. The profiling framework describes a set of interoperable abstract classes referred to processes which constitute a cognitive level for nodes and community of nodes in network. Metrics and parameters, theory and analytical tools to study the coexistence of various type of interaction among nodes, the multiplex dimension of the network and the interplay of collective dynamics and the mesoscale organization are detailed. In addition, in Chapter 6, we have described an evaluation scheme for IoMT microservices, thought of as lightweight applications at edge level in a future 6G scenario, that takes into consideration three main aspects to assess the quality, the acceptability, the usability and the user experience, modulating the output according to the use context. The proposed model, characterized by a multilevel architecture jointly with an analytical methodology based on complex system approach, is composed by different interoperable and chained modules that can assess several aspects of the QoS. The novel approach to design the evaluation scheme follows the similar approach of the object to be assessed thanks to the advent of the 6G paradigm.

- **Is it possible to quantify the impact of human behaviour and dynamics in designing, providing and evaluation of ICT services in a 6G scenario?**
  In Chapter 7 we have introduced two approaches, both analytical and data-driven, to quantify the impact of human behaviours and human-related factors, such as homophily and heterogeneity, in the design of 6G applications. The first approach is focused on the interplay among collective attention, awareness and epidemics spreading in multiplex social networks during COVID-19. The second one is aimed at the definition of new policies, based on reputation score, incentive mechanisms and a DSS, for the designing of policies and mobile crowdsensing systems. Although, the first is referred to an healthcare scenario, the second one to urban applications, both introduce statistical estimators and social predictive markers, such as the awareness reactivity, or the user reputation score for one thing, that measure the impact of past, present and future human dynamics on changing the collective dynamics, on QoS and on timely crisis response, as in COVID-19 pandemics.

- **How can edge nodes trigger cognitive and distributed decision mechanisms, adapting themselves and learning from the environment? How can they tune their dynamics in order to construct the connected and distributed intelligence, optimizing the use of available resources and improving the QoS?**
  In Chapter 8 we have focused on the organizational aspects of MEC severs, assuming 6G scenarios (such as smart city, smart healthcare and WoT) where the intelligence is

shifted to the edge of the network and also the end devices (IoT devices) can act as MEC servers. We have proposed analytical approaches based on multiplex networks, temporal networks and EGT, allowing to focus, at the same time, on social and proximity aspects, and to evaluate cooperative offloading schemes among MECs. Although the constantly changing nature of the environment (and, as a consequence, of service's requests and the computation load) thanks to the additional knowledge extracted from the multiplex dimension of analysis and to EGT, which acts as a reinforcement learning algorithms, MECs acquire a sort of cognition and self-sustaining ability, allowing distributed and cognitive decision mechanisms. Thereby, MEC enable the built of the common and distributed network intelligence at the edge which is pivotal for 6G.

9.2 Concluding Remarks and Future Works

This Ph.D. dissertation has been focused on the design of innovative ICT services, based on the deployment of edge intelligence in 6G through the introduction of an interdisciplinary and bio-inspired approach. 6G networks are a typical example of systems which are in continuous expansion, moving from closed hierarchical or semi-hierarchical structures to open and distributed networked systems, characterized by a high level of interdependence among their very heterogeneous components.
Edge Intelligence is considered as a key pillar aspect of these systems, supporting high performances, new functions, new services and making it possible to satisfy the stringent requirements of the typical 6G use cases. Shifting the intelligence at the edge of the network means bringing some AI features to each end node, or on clusters of nodes, so that they can learn progressively and share what they learn with other edge nodes to provide, collectively, new added value or optimized services.
New topics, apparently disconnected and belonging to different research subjects, become even more central for the design of future mobile communication networks such as social and human related aspects, evolutionary dynamics, emergent behaviours, multiple and complex interactions, interdependences, epidemics spreading, cooperation and so on. For all these reasons, it is crucial the introduction of new approaches to analyse, model and design this networks based on complex systems and on a methodology based on tools such as Multilayer and Multiplex Networks, Evolutionary Game Theory, Epidemic Modelling, but also data analytics, to apply data-driven approaches, collecting and mining user-generated data as digital traces of human dynamics. The literature, properties and features of these tools have been extensively described through the chapters of this thesis.
Furthermore, this dissertation has shown that this approach is particularly suited to include the

dynamic and complex nature of 6G network in technical aspects but also to include social and human aspects in the design of network and services, from mobility to attention, awareness, or reputation. Including and evaluating all these aspects together and their co-evolution allows to define and introduce new parameters, measures, and criteria to classify and evaluate 6G systems, their units and (micro)services, developing metrics capable of combining QoS, QoE, and human perceptions. The multiplex representation together with the evolutionary and reinforcement learning aspects of EGT allows us to study the organizational and learning aspects of edge devices, with the aim at acquiring cognitive capabilities to optimize the computation and the available and common resources, improving the QoS.

In this perspective, the interest of scientific community is shifting towards energy efficient networks, zero energy network resource management, and green computing to meet global sustainability. To this aim, it could be interesting, for the future, deepen the AI algorithms, as machine learning or deep learning, which can be useful in measuring network activity and identifying the actual requirements by analysing the acquired data and identifying trends and patterns from them. In fact, intelligent and real-time network operations in SSNs are facilitated using machine learning techniques which enable fast learning of rapid network changes and dynamic user requirement. Analysing human demand and dynamics, an AI-enhanced system can redirect the resources in real-time and turn on or off the services in accordance with user's demands and behaviours. In addition, with the advent of 6G and edge intelligence, the conventional base stations functions need to be offloaded and moved to the edge to achieve massive low latency communications. This may result in energy barriers at the edge of the networks. In this regard, an interesting research topic to be investigated could be the combined use of AI algorithms and 6G to the design of energy-sustainable and cost-effective computing and communication protocols.

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