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Evolutionary dynamics of MEC's organization in a 6G scenario through EGT and temporal multiplex social network

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Abstract

MEC is considered as a promising candidate to support the deployment of the 6G communication networks, enabling scalability, adaptability and resilience. We propose a modeling approach based on complex system to design a novel organizational aspect of mobile nodes acting as MECs in a 6G scenario, through the introduction of the temporal multiplex social network, which allows us to analyze proximity contacts, by embedding also the social aspects, and the evolutionary game theory. Our findings demonstrate how the proposed model gives a boost to MECs' cooperative behavior, finding out an overall reduction of the blocking probability.

Keywords: MEC; EGT; Temporal multiplex network; Social network; 6G

1. Introduction

Driven by the increasing number of high-resource demanding mobile applications and the shift of communication and computation functions to the edges, mobile edge computing (MEC) is considered as a promising candidate to support the development of the next sixth generation (6G) of communication networks. Ranging from simple sensors to sophisticated devices, and including different network scenarios such as cellular network, vehicular network, Wi-Fi, and Internet of Things (IoT), in order to fulfill the demands of such a heterogeneous, fully connected and intelligent network, the introduction of new approaches and revolutionary network features [1,2] is crucial. Considering that the edges of the network are often populated by hand-held mobile devices, the analysis of the social network dynamics of users' behaviors becomes pivotal. Human beings, their devices and consequently their behaviors act as active elements of the networks. They are changing into a sort of heterogeneous and aggregated things, with a crucial role in technical systems and in the design of the networking functions representing the interacting part of a complex socio-technical ecosystem.

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 [3] and game theory [4], 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.

In this paper, we explore how the temporal multiplex social network [5,6] 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 we propose and show in Fig. 1. We focus 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 [7] sharing of communications and computations resources [8]. Through Evolutionary Game Theory (EGT), we investigate aspects of learning and connections in a multi-tiered infrastructure for the cooperation in terms of

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collaborative offloading and reduction of the whole system's blocking probability.

The paper is organized as follows: in Section 2 we summarize background and methods, in Section 3 we propose our analytical approach, in Section 4 we show and discuss our findings to conclude in Section 5.

2. Background and methods

2.1. Temporal multiplex networks

Complex systems are fully described by the connectedness of their elements interacting with each other via multiple links, which show the topological heterogeneity of many real word systems. In some cases, links are not continuously active but they could represent sequences of instantaneous or interval contacts, like in human proximity networks.

Proximity networks are time-varying graphs representing the closeness among individuals moving in a physical space. They are modeled by interval graphs, which are a particular temporal network [5], based on data about who is close to whom at what time. The huge amount of data available and the various types of interactions, which co-exist and evolve in time, make a description based on the evaluation of temporal and multiplex dimension necessary. This kind of analysis is crucial to quantify how the temporal structure of edge activation and the topology can affect the dynamics of systems interacting through the network.

More specifically, temporal networks, whose edges are intrinsically dynamic and represent interactions, as switching on and switching off links, allow to uncover properties of time-varying networks. Multiplex networks, whose edges belong to different layers, representing several channels of interaction, are able to characterize the structure of many networked real systems [6]. Combining both these representations, each node, has different manifestations in specific layers and in relation to a different time step.

2.2. Evolutionary Game Theory for MECs cooperation

EGT, as traditional Game Theory, is based on the definition of game which is a model of interaction between individuals, and it is described by a set N of players that can choose among a set $A_i = a_{i1}, a_{i2}, \dots, a_{in}$ of strategies; in correspondence of each strategy, players receive a payoff which numerically scores their preference [4].

In EGT, differently from GT, players are not completely rational, as they have limited information about available choices and consequences and strategies evolve over the rounds of the game. In fact, EGT is useful to evaluate the dynamics of changing strategies and it is extensively used to analyze the emergence and evolution of cooperation within a population. To face these issues the so-called social dilemmas have been defined, these are games with two players and two strategies in which collective interests are at odds with private ones. The possible strategies are cooperation and defection, cooperating means contributing to the benefit of the whole population paying a cost; defection means being selfish and exploiting the cooperation of the others [9].

EGT has 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 [4], also applying collaborative offloading schemes: a busy device can count on the collaboration of nearby idle devices to facilitate the task execution [10]. Evolutionary games application allows 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' behaviors will be completely adjusted to the dynamically changing environment, learning which is the most profitable behavior for the whole system.

3. Model

Following the schematic procedure shown in Fig. 1, here we detail the modeling approach based on it. A temporal multiplex network DM $= M^1, \dots, M^T$ is a sequence of multiplex networks, where each M^t with $t = 1, \dots, T$ is a snapshot of the network at the time step t_i, within the time window of observation T [5,11]. A multiplex network M is a network consisting of L layers $l = \{1, \dots, L\}$ and N nodes $i = \{1, \dots, N\}$ 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 $a^\alpha_{ij} = 0$ [6]. 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 $l \in L$ [11].

Taking into account the properties above-mentioned, to analyze the considered scenario we resort to a temporal multiplex network DM composed of two layers α and β, corresponding to different kinds of interactions, populated by aggregated nodes of users and their hand-held devices which act as MECs (see Fig. 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 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 DM we introduce a game theoretic-approach. In particular, we consider the Prisoner's Dilemma Game (PD) [9]. We have simulated the evolutionary dynamics of the PD game 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:

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

A player x on the layer α decides to adopt the strategy S_y of node y playing on the layer β, taking into account the payoff

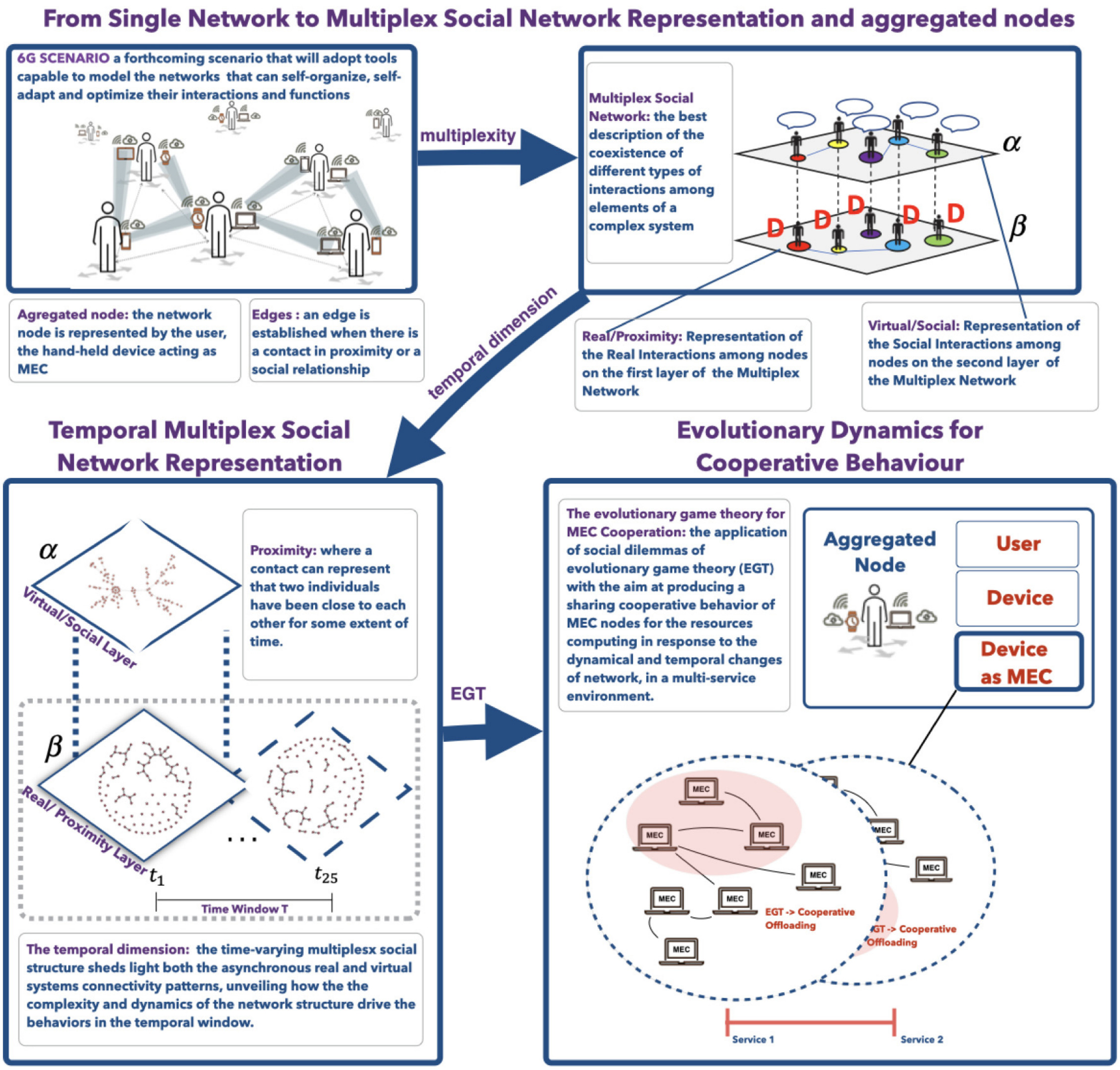

Fig. 1. Evolutionary dynamics for MECs' organization in 6G scenario through temporal multiplex. The figure schematically describes the various steps and key aspects of our modeling procedure, from a 6G scenario to a temporal multiplex representation and the evaluation of cooperative dynamics among aggregated nodes, which act as MECs.

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, 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 [12,13]. Cooperation for nodes in DM means that two MECs exchange each other's computation requests when one of them is overloaded.

To quantify the role of the evolution of cooperation in the computing, we define the blocking probability $P^t_{B_i}$ 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 neighbors:

$$P^t_{B_i} = \frac{1}{k_i^{\vec{m}}} \sum_{j=1}^{N} \sum_{R_n^j = T_j}^{R_k^j} \pi_{R_k^i R_n^j} \cdot \pi_{R_j^*} \tag{2}$$

where $k_i^{\vec{m}}$ is the multidegree of node i [14]; R_n^j 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 DM. T_j is a threshold equal to the number of requests which node j is able to accept. $\pi_{R_k^i R_n^j}$ 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. (1) and the probability to cooperate.

4. Discussion

Simulations have been conducted considering the temporal multiplex network DM consisting of $L = 2$ layers and

Fig. 2. Effects of evolutionary dynamics and time-varying topology on the blocking probability. The figure shows, at the upper side, the number of cooperations for each node (their size) in the time steps t_i, in correspondence to which are shown the density of cooperators (blue) and the blocking probability (gray). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

following the approach described in Section 3 and shown in Fig. 1. Both the layers in DM are composed of $N = 100$ nodes. We model the layer α considering the Scale-free network (SF) [15] 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 DM is observed. Taking into account all these aspects, in the upper side of Fig. 2 we show the timeline of layer β evolution which, for each t_i, represents not only 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' behaviors. In each graph the nodes' size is proportional to its number of cooperations in t_i. At the bottom of Fig. 2 we display both the density of cooperating nodes (in gray) 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 arrive at 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

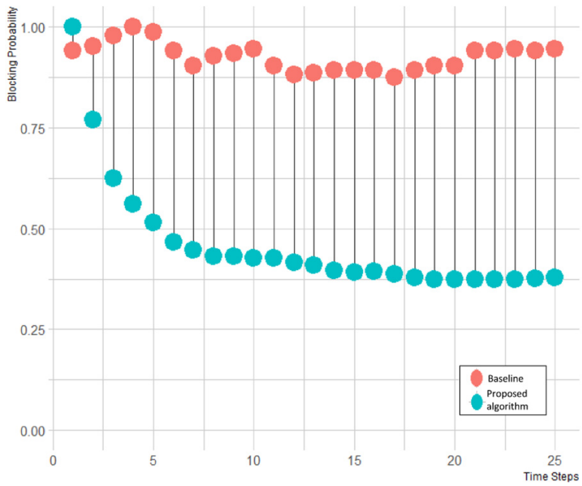

Fig. 3. Comparison of blocking probability Evolution. The dependence of the blocking probability evolution as a function of the application of a baseline case (removing the effect of EGT) and our proposed algorithm.

increase of cooperators density, over the time steps t_i, despite time-varying nature of interactions. EGT, acting as a learning algorithm, gives nodes the opportunity to tune their behavior, 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 has impacts on the global blocking probability P_b gaining higher capacity to provide services. Furthermore, as shown in Fig. 3 starting from the same network hypothesis, we compute the P_b evolution in the t_i time steps by comparing a baseline case with our proposed algorithm application. Since, in the baseline we exclude the EGT effect, in this case we shed light on a constant maintenance of the P_b values during the time window T. Differently, by using our proposed algorithm the competition dynamics jointly with the multiplex structure has impact on the P_b dynamic trend, lowering its mean value and decreasing its values in time.

5. Conclusion

In this paper we propose a theoretical approach based on temporal multiplex networks and EGT. The former allows to focus, at the same time, on social and proximity aspects, the latter to evaluate the evolution of cooperation among MECs. We demonstrate that, although the constantly changing nature of environment and interactions, the introduction of EGT, acting as a learning process, allows MECs to self organize in order to reduce the global blocking probability. Thereby, MEC enables the build of a common and distributed network intelligence, which is considered a pivotal point for the deployment of the next 6G communication networks.

CRediT authorship contribution statement

Barbara Attanasio: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing, Visualization. **Aurelio La Corte:** Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing, Visualization. **Marialisa Scatà:** Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing, Visualization.

Declaration of competing interest

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

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