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Self-organization in multilayer network with adaptation mechanisms based on competition

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ABSTRACT

The paper considers the phenomena of competition in multiplex network whose structure evolves corresponding to dynamics of it's elements, forming closed loop of self-learning with the aim to reach the optimal topology. Numerical analysis of proposed model shows that it is possible to obtain scale-invariant structures for corresponding parameters as well as the structures with homogeneous distribution of connections in the layers. Revealed phenomena emerges as the consequence of the self-organization processes related to structure-dynamical self-learning based on homeostasis and homophily, as well as the result of the competition between the network's layers for optimal topology. It was shown that in the mode of partial and cluster synchronization the network reaches scale-free topology of complex nature that is different from layer to layer. However, in the mode of global synchronization the homogeneous topologies on all layer of the network are observed. This phenomenon is tightly connected with the competitive processes that represent themselves as the natural mechanism of reaching the optimal topology of the links in variety of real-world systems.

Keywords: Multiplex network, complex network, Kuramoto model, synchronization, competition

1. INTRODUCTION

Many real world structures of different nature can be described as graphs or networks, where the units are the nodes of the network and the relationships between them represent the connections or interactions between nodes. This approach to study of the evolutionary processes in network's structure allows to obtain fundamental knowledge about the processes that take place in technological,[1–4] biological,[5–7] social[8,9] and urban[10–12] systems, and also is capable to increase our understanding of functioning of the neural networks of the brain,[13–16] which also may be useful in fields of robotics and designing of intelligent robotic systems.[17,18]

The interest to studying the network structures of the real world causes the active development of variety of methods and emergence of new theories and approaches. One of most modern and effective approach to study this issue is to build a complex (or multiplex) network model, where each layer contains identical set of nodes that are connected with different types of links (see Fig. 1). This model is widely used to describe the networks where topology of the links has a nonstationary character, which in combination with it's flexibility allows to describe various systems in different fields of nature.[19,20] In particular, in field of neuroscience this approach is used to study synchronization between the neurons on local scale as well as the global synchronization between the different regions of the brain.[21–24]

The recent studies revealed that, despite the fundamental differences between the above mentioned systems, the multiplex approach revealed that they have a certain number of similar properties: (a) the power-law distribution of weights of the connections between the nodes; (b) coexistence of the module structures on macroscopic scale. Recent studies has shown that these properties are caused by the self-organization processes that also take place in the real-world complex networks. These properties represents themselves as the consequence of

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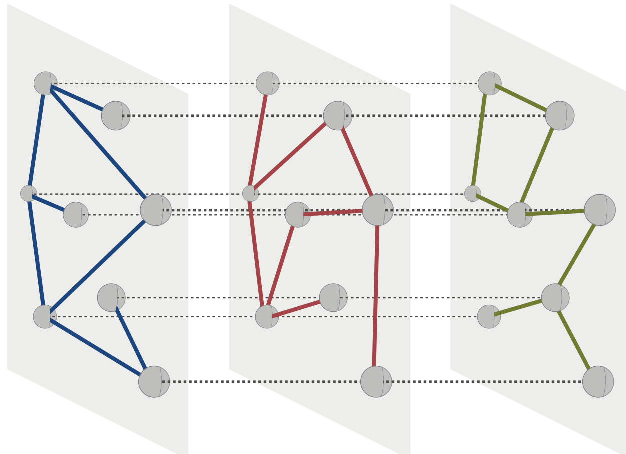

Figure 1. The architecture of multilayer network with identical set of nodes on each layer and different topologies of the connections between them. The competition between the layers occurs in the self-learning process and manifests itself in emergence of specific topological patterns.

self-learning, i. e. changing topological properties of the network under influence of the two fundamental mechanisms.[25] First is the homophily[26] — the tendency of the units to reinforce their connections with other units of the network which behave similarly. The second is homeostasis,[27] that stands for the limitation of the resources for each node of the network for sustain its connections. Emergence and coexistence of these two mechanisms provides competition between the layers for the optimal topology and affects intra-layer pattern formation in adaptive multiplex network.

In our study we focus on competition between layers of self-learning multiplex network for optimal topology and formation of specific intra-layer patterns observed in systems of real world. We consider the multiplex network model of Kuramoto oscillators[28] that proved itself as an effective approach to describe dynamical processes in many existing systems.[29,30]

2. METHODS

This paper considers the structure and dynamics of the multiplex network based on classic Kuramoto model consisting of $M = 2$ layers with $N = 500$ nodes on each layer. Dynamical state of u-th node on layer l is defined by

$$\dot{\varphi_u^l} = \omega_u^l + \lambda \sum_{j=1}^{N} w_{uj}^l sin(\varphi_u^l - \varphi_j^l), \tag{1}$$

where ω_u^l is natural frequency of node u on layer l chosen randomly in range [-π; π], λ is a coupling strength, w_{uj}^l — the weight of the link between two nodes u and j on layer l that behaves in accordance with equation $\sum_{j \neq i}^{N} w_{ij}^l = 1$, i. e. sum of all incoming intra-layer connections of the node remains constant in time, which is mathematical reflection of homeostasis. At the same time, the weight of the connection between two nodes u and j evolves in time according to:

$$\dot{w_{uj}^l} = p_{uj}^l - \Big(\sum_{k \in N^l} p_{uk}^l\Big) w_{uj}^l - \Big(\sum_{k \neq l} p_{uj}^k\Big) w_{uj}^l, \tag{2}$$

where the time dependent value p_{uj}^l is defined by

$$p^l_{ij}(t) = \frac{1}{T}\left| \int\limits_{-\infty}^{t} e^{\left(\frac{t-t'}{T}\right)} e^{\left(i\left[\varphi^l_u(t)-\varphi^l_u(t')\right]\right)} dt' \right|, \tag{3}$$

3. RESULTS

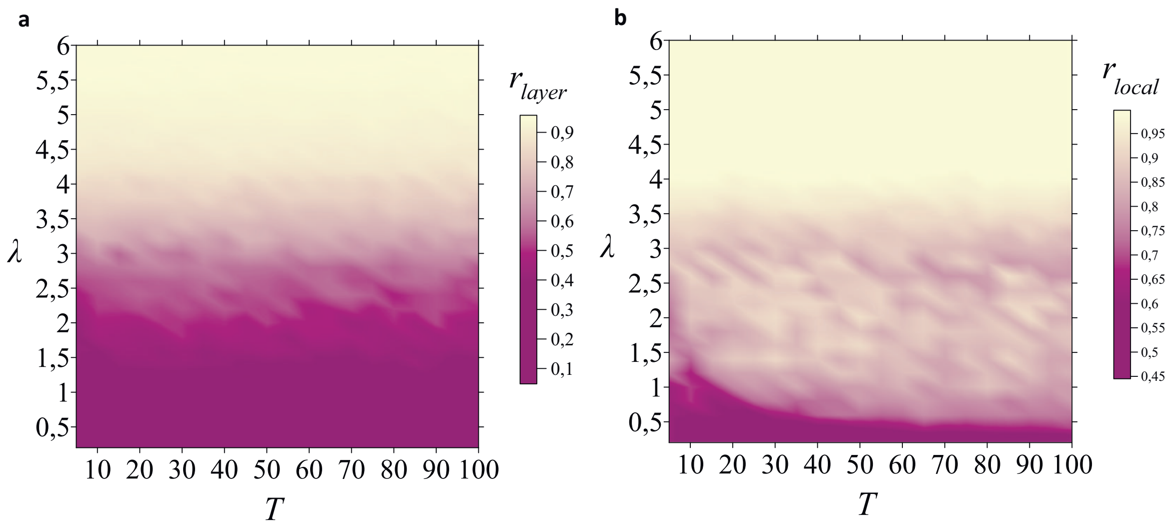

Figure 2. Two-parameter dependencies of the order parameters r_{layer} (a) and r_{local} (b) from the control parameters: coupling strength λ and self-learning time T.

In order to reveal the mechanism of self-learning based on combination of homeostasis and homophily principles the numerical analysis of dynamical processes in developed model with changing the control parameters — self-learning time T and coupling strength λ — was conducted. The characteristic of averaged level of synchronization of phase oscillators inside the layer r_{layer} was introduced:

$$r_{layer} = \frac{1}{MN}\sum_{l=1}^{M}\left|\sum_{u=1}^{N} e^{i\varphi^l_u}\right|, \tag{4}$$

and r_{local} that defines the level of synchronization between any two nodes in the network on each layer, averaged over all pairs of coupled elements:

$$r_{local} = \frac{1}{MN}\sum_{l=1}^{M}\sum_{u=1}^{N}\sum_{j=1}^{N}\left(w^l_{uj} e^{i\left[\varphi^l_u-\varphi^l_j\right]}\right), \tag{5}$$

The total difference between adjacency matrices of the layers was also calculated; this parameter allows to characterize the inequality in the layers topologies:

$$w_d = \sum_{u=1}^{N}\sum_{j=1}^{N}\left|w^1_{uj} - w^2_{uj}\right|, \tag{6}$$

Fig. 2 represents two-parameter dependencies of order parameters from λ and T. The small values of control parameters are corresponding to the mode of asynchronous dynamics — both averaged on all layers r_{layer} and averaged degree of synchronization between all coupled elements in the network r_{local} take small value. However,

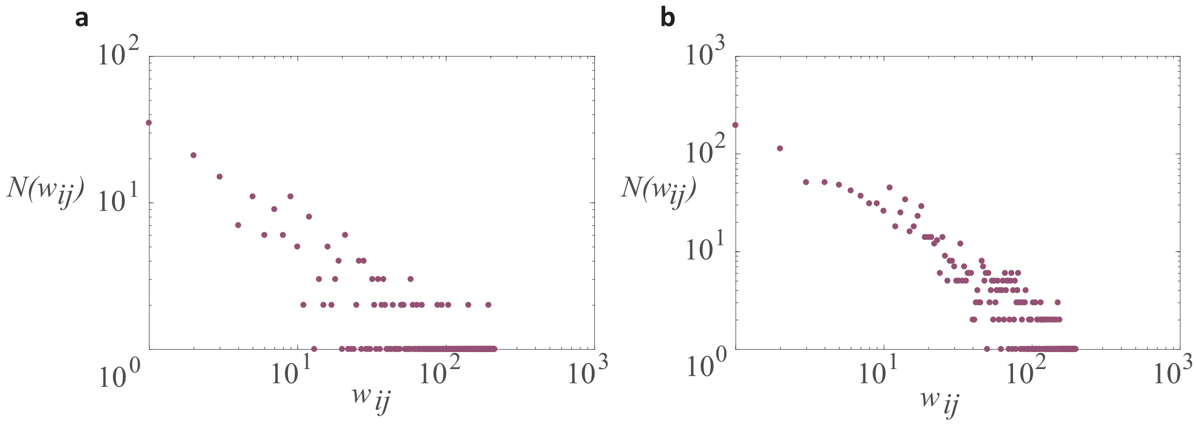

Figure 3. Degree distribution of connection's weights of first (a) and second (b) layers of the network with $\lambda = 1.6$ and $T = 50$

with growing of the time parameter T the differences between the order parameters begin to appear. One can see that parameter r_{layer} (see Fig. 2,a) shows weak dependence from T, changing only with increasing of coupling strength λ. At the same time, r_{local} (see Fig. 2, b) grows much faster, which indicates of enhance of the synchronization between connected nodes during the self-learning time.

Increasing couple strength leads to establishing of the mode of partial (or temporal) synchronization inside the network's layers. This mode corresponds to small values of r_{layer} and high level of local synchronization of elements r_{local}, which is also indicates of emergence of synchronized clusters inside the network.

In order to obtain the confirmation of results described above, we show the probability distribution of weights of connections for both layers with $\lambda = 1.6$ and $T = 50$ (see Fig. 3), where the order parameters are significantly different ($r_{layer} < r_{local}$). The distribution obeys a power-law, which means that with current values of control parameters the network structure reaches scale-free topology, that is inherent in the absolute majority of real networks. Observed local maximum and minimum that are deviating from the general trend are corresponding to the nodes that are part of the strongly connected inside but weakly interacting with each other homogenous clusters, which represents modularity property of real-world systems.

4. CONCLUSION

The study of the model of self-learning multiplex network that demonstrates competitive interaction between the layers was conducted and various forms of collective dynamics of the elements were revealed. In the mode of partial and cluster synchronization the dynamical process of self-learning leads to formation of free-scale topologies with complex structure that are different on each layer, which is connected with competition between the layers. At the same time in the mode of global synchronous dynamics the network is characterized by the appearance of a homogeneous topology on the layers. The further research of the principles of competition and self-learning in complex networks will allow to enhance understanding of processes that take place in real systems. Moreover, revealed patterns may be used in various applicative technologies including artificial intelligent and robotics.

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