Building self-organizing information and telecommunications systems

A A Sukonschikov, A N Shvetsov, I A Andrianov and D V Kochkin
Vologda State University, 15, Lenin str., Vologda, 160000, Russian Federation

E-mail: avt@vogu35.ru

Abstract. The article discusses the foundations of the functioning and evolution of complex distributed information and telecommunication systems in the neuro-fuzzy agent-based paradigm. The principles of formalization of this class of systems are proposed. The concept of a distributed intelligent information and telecommunication system is introduced, as a geographically distributed multi-level hierarchical set of hardware and software controlled by an agent-based system.

1. Introduction
The increase in the complexity of multi-agent interaction and management in information and telecommunication systems (ITS) is caused by the growth of ITS volumes, changes in the topology of connections, delays in determining the state of intelligent agents (IA) and ITS. Therefore, research is required on the possibilities of interaction, organization and self-organization of IA in self-developing communities that manage the functioning and development of ITS with the required information processing quality indicators, based on models of fuzzy and neural AI.

The multilevel system organization of ITS includes software and hardware components that are subject to software and hardware-software control, configuration and modification. In the process of ITS development, the network architecture can change (adding and removing segments). There may also be changes in the composition of telecommunications equipment, the number and composition of workstations, the parameters and nature of traffic, the priorities of the tasks being solved, global and local optimization criteria.

The scale and speed of the desired changes require reducing the influence of the human factor on the processes of modernization and improvement of ITS. Thus, the problem arises of constant and timely improvement of ITS, reconfiguration of the architecture of computer networks, adaptation to the changing requirements of both the internal and external information environment.

This problem forms a logical requirement for self-improvement and self-development in the process of operation and modernization of ITS, in the development of new functionalities in accordance with the requirements of users, the structure and characteristics of tasks being solved, and the features of the computing environment.

In modern systems theory, self-organizing systems are usually called systems that have the ability to increase their internal order and change their organization. This formulation goes back to the well-known work [1], which is considered the first publication dedicated to the problem of self-organization in cybernetic systems. In this article, W.R. Ashby argues that a machine can be self-organized, that is,
be deterministic and at the same time capable of spontaneous changes in its internal organization. The concept of self-organization was later developed by Ashby in [2].

Subsequently, a number of concepts were introduced in the field of synergetics, and models were developed to explain the mechanisms of self-organization. In the formulation of G. Haken [3], self-organizing systems are characterized by the ability to form macroscopic structures described by adequate order parameters.

According to [4], self-organizing systems have a number of features due to the presence in the system of active elements that ensure the adaptability of the system to changing environmental conditions, but at the same time form uncertainties preventing deterministic control of such a system.

These features, specific for the class of ITS considered by us, are as follows:

- non-stationarity of many parameters of the ITS, and the stochastic nature of behavior;
- the need and ability to adapt to the changing conditions of the external infocommunication environment and resist the effects of interference and deliberate external resistance;
- the fundamental non-equilibrium and uncertainty of the global states of the system; the main parameters of the ITS are fuzzy;
- the ability to resist entropic processes that destroy the system and form negentropic processes that ensure the restoration of the structure and main indicators of the ITS functioning;
- the ability to form scenarios of the behavior of active components of the ITS, to change the software and hardware structure of the system, ensuring the established performance indicators;
- the ability to form the internal goals of active components of the ITS, corresponding to the general goals of the system and the tasks set by the users of the ITS.

2. Principles of structures and processes formalization of ITS self-organization and self-development in the neuro-fuzzy agent-based paradigm

Self-organization problems in relation to agent-based systems (ABS) and multi-agent systems (MAS) were studied in a number of works [5-8]. According to the theses formulated in [5, 7, 8], two classes of self-organizing systems can be distinguished. Self-organizing systems, in which there is no explicit external management and internal centralization of management, are usually called strong self-organizing systems. MAS, in which there is explicit internal (centralized) control, are called weak self-organizing systems [5].

The agent-based ITS (AB ITS) considered by us should be attributed to the class of weak self-organizing systems, since they necessarily have centralized control, which is distributed to varying degrees across the levels of ITS presentation.

The following basic properties are attributed to self-organizing systems [5]:

- autonomy, i.e. lack of explicit control from the external environment;
- global order (organization, structure), which arises in the system due to the internal local interactions of its components;
- emergent properties, i.e. properties that are observed only at the meta-level and are not derived from the observation of the individual behavior of components;
- dissipation, i.e. energy dissipation in unstable states of the system in the absence of external disturbances, which leads to transitions of the system to some stable states, in which its emergent properties can be observed;
- nonlinear dynamics, instability and sensitivity to initial states and small changes in parameters, when at their small fluctuations at some critical points of the state space the behavior of the system can change significantly, and this property cannot be derived by studying the properties of individual components and their interactions;
- plurality of stable states (attractors, points of attraction);
• redundancy of components and their interactions, which leads to system insensitivity to local damage to its components (fault tolerance);
• adaptability, i.e. the ability to change their behavior and move to a new stable state when changing the organization of the system and the external environment;
• complexity due to the fact that self-organizing systems usually consist of a large number of autonomous components, and their global properties and behavior are not reduced to a combination of individual properties of components;
• the presence of a hierarchy; a self-organizing system is described at least at two levels, namely, at the level of local interactions of components, and at the meta-level, at which its emergent properties are described.

By now, some variants of using self-organization methods in ITS are known. Routing protocols based on self-organization MAS in MANET (Mobile Ad Hoc Networks) have been studied in sufficient detail. Due to the dynamics of the nodes composition and the network topology, the usual methods of packet routing do not work because the dynamics of the network topology requires continuous adaptation of the routing tables, which is not provided for in conventional networks. To take into account the dynamics of the network topology in the routing processes, it is necessary to somehow inform all nodes about the changes that have occurred in the network. This requires additional resources, especially when the recalculation of routing tables needs to be performed quite often.

Similar problems arise in overlay (virtual) networks built on the basis of paired interactions (in P2P networks), in which each agent can directly communicate only with a limited number of neighboring nodes (at the application level), and it does not have information about routes to other nodes. Such networks often also have a dynamic composition and topology. With a large network, the problem of the complexity of routing algorithms can become almost insurmountable. This makes it necessary to search for new principles of routing control.

To date, several routing protocols have been proposed, which are based on the ideas of self-organization in the MAS. The general idea behind them is as follows. The so-called “ant packets” are sent in some proactive manner in order to continuously build the current selection of possible paths and update the routing tables in the nodes of the system in real time. Ant packets travel through the network, leaving on their way information similar to that carried by the pheromones of ants.

In this case, the probability of choosing a particular route by other packets is set by a value proportional to the concentration of such a digital pheromone on it. In this way, a distributed study of the environment is implemented based on the paradigm of accumulation and evaporation of pheromone. It leads to the dynamic creation of emergent structures that form the routing tables.

Among the known protocols of this type, the ABC, Ant-Net, and AntHocNet protocols should be noted [9]. These protocols provide high robustness to errors in some nodes, the ability to balance the load of communication channels, and good adaptation to the dynamics of the network topology and the composition of its nodes. The AntHocNet protocol studies the dynamics of a network using information that is gathered based on solutions of current routing problems, as well as using proactive measures. For these purposes, agent $A$ is installed in each node of the network, which is responsible for dynamically updating the routing table. Agent $A$ has a list of destination nodes to which it has previously sent messages. Some of the nodes in this list are its neighbors. Such nodes are directly reachable in a wireless communications environment. For each node known to agent $A$, a vector of floating point values is specified. The number of components of this vector is equal to the number of neighbors of the node. The vector components define the intensity of the digital pheromone on the way to each neighbor, provided that the message is addressed to a node that may not be a neighbor.

In other words, if it is necessary to transfer a message from node $A$ to a node known to it, this message is transmitted through one or another neighbor, which is determined using a random mechanism. This mechanism implements a probability distribution on a set of neighbors, the components of which are proportional to the values of the corresponding components of the vector. Thus, the routing table at node $A$ is a $m \times n$ table of digital pheromone values, where $m$ is the number of nodes known to the agent at
node $A_i$, and $n$ is the number of its neighbors. In this case, the pheromone value in the cell $<i, j>$ of the routing table determines the assessment of the viability of the path to the destination node $A_i$, which passes through the neighbor $A_j$. Since the topology of the network can change over time, the value estimate must be dynamically updated during the operation of the network. This is accomplished by using what are called reactive and proactive ant packets.

An overlay network is usually understood as a virtual network, the structure of which differs from the real communication network on the basis of which this overlay network operates. In it, each autonomous entity usually has many neighbors, with which it can communicate “directly” by name, as it appears to it within the overlay network. For its interaction with other entities of the overlay network, it is necessary to use one or another distributed search mechanism.

This overlay network does not “know” anything about the existence of a communication network and its structure. It also does not know how its direct interaction with neighbors is implemented and how a distributed search for answers to queries is performed within the overlay network. At present, the architecture of building information systems using the metaphor of the overlay network is considered as one of the promising architectures, which has many practical implementations and has proven itself well.

To support the operation of overlay systems, interaction protocols implemented within a special infrastructure can be used. This infrastructure completely separates the application layer from the communication layer and thus provides support for interoperability in overlay networks.

In [10], a self-organizing T-man protocol was proposed and investigated for managing the topology of an overlay network, namely, for optimizing the topology as applied to solving a particular infrastructure or applied problem in the network. The problem statement considers a large-scale network with a dynamic architecture, in which each node knows about the existence of only a relatively small number of other nodes in the network.

It is assumed that the dynamics of the network and the number of its nodes are such that it is unrealistic to obtain complete knowledge of the nodes, even if there were means that are designed specifically for this purpose. Depending on the task (or tasks) that is being solved in this network, it is important to answer the question: who knows about whom? The answer to this question may be completely independent of the physical structure of communications. This situation is typical for overlay networks. The answer to the question posed determines the quality of solving certain problems. But this question can be posed differently: who should know about whom in order for the task to be solved in the best possible way? The search for an answer to this question determines the class of tasks, which are commonly referred to as configuration tasks for the overlay network. This is exactly the task that the T-man protocol solves. This protocol implements a simple, robust algorithm that works well for high-dimensional problems. The problem is solved in the context of the requirements for the simplicity of the algorithm, its robustness, adaptability, and also applicability to problems of large dimension.

The protocol is based on the use of the so-called ranking function, according to which each network node orders its neighbors according to their usefulness in relation to the quality indicator of the current network topology. In this paper, we consider a simple ranking function that expresses the concept of distance in a certain space of attributes, which are determined by the meaning of the concept of optimality for the network topology. This function is used by a node to update the neighbor list by removing the least useful neighbors and replenishing it with a subset of its best neighbors in accordance with the ranking function. This algorithm is implemented using the Gossip protocol.

The results of the analysis of existing approaches and methods for constructing AB ITS make it possible to substantiate the principles of formalizing the structures and processes of self-organization and self-development of ITS in the neuro-fuzzy agent-based paradigm. In order to determine the principles of formalizing the structures and processes of self-organization and self-development of ITS in the neuro-fuzzy agent-based paradigm, we will list the main tasks that must be solved:

- assessment of current situations arising at different levels of management based on fuzzy logic;
- forecast of changes in the current situation at different levels of AB ITS;
• forecast of changes in the current values of monitored QoS characteristics;
• development of management actions at all levels of AB ITS;
• evaluation of events and the current value of resources at the object level;
• transmission of control and information signals between agents of the same and different levels;
• simulation situational modeling of the corporate network functioning at the structural level.

To solve the above problems, a mathematical apparatus is required that combines the capabilities of fuzzy logic, neural networks, and also has developed verification methods for models built on this apparatus. The mathematical apparatus of integrated attribute Petri nets (IAPN) developed by the authors has such capabilities. More details about it can be found in [11].

The main principles of the development of the mathematical apparatus of the IAPN are:

• convergence of predicate-transition Petri nets (PN), fuzzy PN and fuzzy logic, which allows to build a new subclass of fuzzy PN;
• convergence of predicate-transition PN, fuzzy PN and artificial neural networks, which makes it possible to build a new subclass of neural PN;
• convergence of a new subclass of fuzzy PN and other extensions of PN, which allows to build a new subclass of attribute PN;
• modularity of construction of individual agents on the subclass of Petri nets extension corresponding to the given agent in terms of functionality,
• integration of all modules based on the general properties of the subclasses of Petri nets.

The modularity consists in the development of the following modules of IAPN:

• modules based on the introduced subclass of fuzzy Petri nets for assessing current situations, events and the value of resources, as well as developing control actions at all levels of the situational intelligent agent model;
• modules based on the introduced subclass of neural Petri nets for predicting changes in the current situation at different levels of the situational intelligent agent model, as well as predicting changes in the current values of monitored QoS characteristics;
• modules for simulation of agents of functioning in corporate network devices at the structural level based on the introduced subclass of fuzzy attribute Petri nets;
• modules of interconnection between the above modules based on the introduced subclass of fuzzy Petri nets.

A common property of all IAPN modules developed by the team is the ability to process fuzzy data. Therefore, for the integration of all modules, the special attribute of the IAPN label is used – the degree (function) of membership.

Verification methods such as the matrix method and the reachability tree method can be applied for all the developed subclasses of the IAPN.

3. Conclusion

For the construction of AB ITS, new principles have been formed to which such systems must comply: the principle of goal structuring, the principle of agent orientation, the principle of hierarchical intellectual organization, the principle of modularity of intelligent agents; the principle of structural and functional flexibility of intelligent agents, the principle of a unified mathematical apparatus, the principle of self-development and evolution of the system.

The implementation of the proposed principles presupposes the development of situational modeling of ITS by adding additional event and structural levels to each situational level [12]. The event level reflects all the events occurring in the AB ITS model. The structural level reflects the internal structure
of the ITS and allows one to perform simulation modeling to obtain the results of the possible functioning of the AB ITS under various behaviors of the infocommunication environment. When building the AB ITS with support for quality of service, further research of the ITS behavior at the following levels of system representation is assumed: the level of simulation modeling (the level of the structural scheme of the network), the level of local control systems (object level), subnet management level based on the analysis of situations that have developed at the subnet objects, and corporate network management level.

For the subsequent self-organization of AB ITS, the authors of this article proposed a method for synthesizing predictive models that support decision-making in managing complex information and telecommunication systems based on two types of applied ontologies: information system ontology and agent-based model ontology [13]. The use of the proposed approach will allow to develop software interfaces for the integration of agent-based models and information systems that can provide the solution of problems of identifying objects of one system in another. This makes it possible to interpret the results of specialized functions performed by them, and also to synthesize sets of item instances of one system based on information contained in another system. At the stage of synthesis of an agent-based model, the presence of a meta-ontology makes it possible to combine modules of behavior models of the same components defined in different subject ontologies.

References
[1] Ashby W R 1947 Principles of the Self Organizing Dynamic System General Psychology 37 125-8
[2] Ashby W R 1962 Principles the self-organizing system Principles of Self-Organization: transactions of the University of Illinois Symposium (London: Pergamon Press) p 255-78
[3] Haken H 2005 Information and self-organization Macroscopic approach to complex systems (Moscow: ComBook) p 248
[4] Knyazeva E N and Kurdyumov S P 2007 Synergetics: Non-linearity of time and landscapes of co-evolution (Moscow: ComBook) p 272
[5] Bernon C, Chevrier V and Hilaire V 2006 Applications of Self-Organising Multi-Agent Systems: An Initial Framework for Comparison Informatica 30 73-82
[6] Gardelli L, Viroli M and Casade M 2007 Designing self-organising environments with agents and artifacts: a simulation-driven approach Agent-Oriented Software Engineering V 2(2) 254-71
[7] Gorodetsky V I 2012 Self-organization and multi-agent systems I. Models of multi-agent self-organization RAS Proceedings Control theory and systems 2 92-120
[8] Gorodetsky V I 2012 Self-organization and multi-agent systems II Applications and development technology RAS Proceedings Control theory and systems 3 102-23
[9] Boztepe I S and Erdur R C 2018 Linked Data Aware Agent Development Framework for Mobile Devices Appl. Sci. 8(10) 1831
[10] Jelasity M, Montresor A and Babaoglu O 2009 T-MAN: Gossip-based fast overlay topology construction Computer Networks 53 2321-39
[11] Sukonshchikov A A, Kochkin D V and Shvetsov A N 2019 Fuzzy and neural Petri nets (Kursk: University book) p 209
[12] Sukonshchikov A, Kochkin D, Shvetsov A, Andrianov I, Sorokin A and Rzheutskaya S 2020 Modeling the Elements of an Enterprise Infocommunication System Using Colored Petri Nets Conf. of Open Innovations Association FRUCT 26 660-6
[13] Shvetsov A N and Dianov S V 2019 Using ontologies in the synthesis of agent-based models of complex systems Materials of 9 Int. Sci. and Pract. Conf. Perspective development of science, technique and technology (Kursk: South-West State Univ.) 344-7