

Review Article

Self-Organization in Network Sociotechnical Systems

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We can observe self-organization properties in various systems. However, modern networked dynamical sociotechnical systems have some features that allow for realizing the benefits of self-organization in a wide range of systems in economic and social areas. The review examines the general principles of self-organized systems, as well as the features of the implementation of self-organization in sociotechnical systems. We also delve into the production systems, in which the technical component is decisive, and social networks, in which the social component dominates; we analyze models used for modeling self-organizing networked dynamical systems. It is shown that discrete models prevail at the micro level. Furthermore, the review deals with the features of using continuous models for modeling at the macro level.

1. Introduction

The ability to self-organize is one of the key features of dynamic network systems. This quality is most evident on social media, in network communities, ecosystems, and various structures of the sharing economy.

There are several factors affecting the growth of socio-technical systems, which provided room for interaction between entities of various nature: humans, intelligent devices or agents, and robots. Among them are the contemporary stage of interaction process automation; a surge in smart devices, intelligent equipment, and robots; and the development of artificial intelligence and machine learning. Even on traditional social media platforms, there are myriads of digital objects acting in the name of a human user.

Dynamic network systems, including those that can be attributed to sociotechnical systems, are usually focused not on rigid management systems but on the introduction of self-controlling, flexible, scalable, and distributed structures [1–3].

The idea of self-organization was formed a long time ago. Thus, R. Descartes put forward the hypothesis of self-organization as an ordering in the system due to its internal dynamics. W.R. Ashby formulated principles of the self-organizing dynamic system in 1947. The founder of synergetics, H. Haken, defines it as the science of self-organization.

The modern development and popularity of social networks and network communities has caused new, intensive research in the field of self-organizing systems, which is associated with the development of technologies that not only allow observing and analyzing the dynamics of social and economic systems but also developing applications for solving practical problems of influencing the audience of networks and the processes occurring in them.

Features of interaction in modern network systems, the dynamics of the processes occurring in them, and the principles of self-organization are not fully studied today.

Software agents became important participants of Internet communities in addition to humans. When the agents

have emerged as full participants in the processes, the term “Internet-of-agents” came into use [4, 5].

Multi-agent systems [6, 7] have shown that self-organization is effective when it comes to solving problems in various sectors such as transportation [8–11], logistics [12, 13], electric power [14, 15], e-commerce [16–18], health care [19], social services [20], etc.

The systems also revealed many problems that arise when self-organizing distributed systems are implemented, such as distributed problem solving, coordination and alignment, ethics and communication, as well as reliability and stability in critical states. For heterogeneous multi-agent systems, where the agents are designed by different developers, as well as for human-agent systems, the ethical rules for the agents [21–23] and their enforcement are crucial for interaction and problem-solving. The importance of these problems is shown in Ref. [23]. Evidently, ethical consequences of the present and future activities of the smart devices are vital, and we cannot be sure that intelligent autonomous devices would follow certain ethical rules. This prompts further research into machine ethics, as well as the ethics of the new technological stage as a whole.

Since the Internet of Things was introduced, network processes have featured smart things and tools. This calls for the development of new models, where smart things and tools are the end customers, signaling an imminent transition to a new stage, with self-organizing distributed systems being the foundation for the future organizational design.

Nowadays, “ecosystem” is one of the most frequently used terms in business. According to the complexity theory, an ecosystem is a complex of self-organizing, self-regulating, and self-developing systems. The models of biological ecosystems are admittedly essential in business applications because the principles of self-organization are crucial for the development of modern business and industrial structures. These artificial digital ecosystems are highly complex, indeterminate, and dynamically nontrivial. As of today, there are no theories that can give us an accurate understanding of their features, dynamics, and control of processes in them.

For self-organizing networked digital systems that control complex industrial processes, there are several issues to be addressed first: supporting the interactions between the participants following the process goals, observing the dynamics, and guaranteeing the stability of interactions. This, in turn, calls for improved methods to ensure process stability. Those methods should allow us to predict, reveal, and distinguish any critical phenomena in the system, which might lead to malfunction or even destruction of the systems, and subsequently to find ways to mitigate the adverse effect of those processes.

Critical phenomena in physics, thermodynamics, and other related fields include numerous anomalies observed at the points of second-order phase transition. Phase transitions describe the physical processes of transition from a medium state defined by a set of parameters to another state with another set of parameter values, and in thermodynamics, the critical point is the end point of the phase coexistence curve in which phases the thermodynamic equilibria become identical in their properties. The classical theory of phase transitions was formulated by Landau and Lifshitz [24].

With the development of global networks and corporate networks, the study of dynamic processes and critical phenomena in disordered systems was also extended to network structures. Interest in the study of networks in this context is associated not only with a large number of their practical applications but also with the peculiarities of the inhomogeneity and fluctuations that arise in them.

In self-organizing digital network systems, the processes are led by machine-to-machine or human-to-machine interactions, with data entry and interpretation errors elimination being one of the major problems. The development of the robotic process automation (RPA) software designed to automate business activities formerly performed by humans, chat bots, and various recommendation systems helped to limit critical phenomena due to adverse effects of the aforementioned factors. However, there are still many problems where distributed resources and distributed problem-solving processes are not controlled efficiently enough, giving rise to critical phenomena.

Machine-to-machine interactions are dominated by signal and data transfer protocols. On the contrary, human-to-machine and human-to-human interactions are mostly performed through exchange of short messages, like in microblogging online communities. The data that need transferring in big volumes are picked from various existing data sources. The answer options could also be picked from a fixed set in a multiple-choice format. The critical phenomena that arise here could be caused by many factors, such as an untimely or incorrect response to a query, lack of requested information, mass-mailing of queries or opinions in the course of distributed problem solving, etc.

Modern networked dynamical systems are quite complex in technological and organizational aspects; therefore, controlling them creates multiple nontrivial challenges [25, 26].

This review examines two types of digital distributed systems: production systems and social networks.

In modern and promising concepts for the development of production systems, the technical component is the game changer; however, self-organization is considered a key characteristic of such systems, and decision-making and management in such systems are largely based on artificial intelligence methods and the study of the behavior of human communities.

Social networks are dominated primarily by the social component, although they have a complex and developed technical infrastructure and many digital objects.

2. Research Method

This systemic overview is an interdisciplinary study devoted to the development of network sociotechnical system self-organization models, with a focus on analyzing the use of these models in industrial systems and on social media. The main purpose of the review is to assess the current state and prospects of self-organization models in relation to the network sociotechnical system. The field under consideration is interdisciplinary, covering areas of application in computer science, physical sciences and engineering, and the

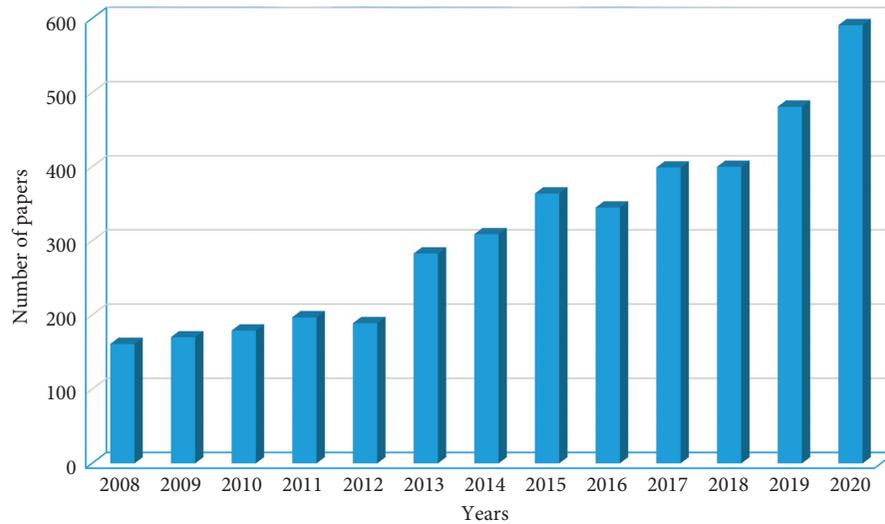


FIGURE 1: Papers published in the mentioned years.

social sciences. Although there has been a lot of self-organization research conducted over the years, the development of digital technologies has had a significant impact on the introduction of self-organization into modern systems. These aspects were the main reasons behind the choice of literature.

The overview rests on the literature accessible in Web of Science and ScienceDirect databases through the protocol PRISMA-P (Preferred Reporting Items for Systematic reviews and Meta-Analysis Protocols) [27].

English-language sources were mainly used to search for references, with the following keywords: (1) self-organizing sociotechnical system, (2) digital distributed manufacturing system, (3) social networks, (4) mathematical dynamics and modeling of self-organizing systems. We considered scientific articles, reviews, conference proceedings, and book chapters for the period 2008–2020. The subject fields were limited to Computer Science, Social Sciences, and Engineering. The initial search yielded around 4,000 scientific papers (see Figure 1). We can clearly see the global scientific community's growing interest in the subject.

To pick out the most academically valuable papers, we used additional criteria: publication level (a journal must fall into the first or second quartile of Web of Science) and citation index (a paper must be cited at least twice a year). To select the basic part of the list of publications, we compiled a thesaurus, including terms characterizing research areas associated with self-organizing systems, as well as with existing and promising digital technologies. When selecting basic resources, we factored in the bibliometric data related to authors (citations, number of cited publications), institutions, publisher, journal, and country. We then carried out an additional search based on the selected key topics; we sought to select the most significant publications, to show a retrospective of research, and to find interesting new studies that are often presented at conferences and workshops. Also, for the sake of completeness, we included a set of classic scientific papers and older monographs.

Four experts were involved in searching for and selecting the papers. One of them was responsible for the initial search, selection, and retrieval of bibliometric data and abstracts. Then, other researchers performed the expert selection of papers based on the aforementioned criteria. The full text of all picked papers was read and reviewed by each member of our research group. Outside experts were invited to resolve disputes.

More specific subjects—for which the papers were selected and organized—were defined and they formed the backbone of our review:

- (i) Principles of operating self-organizing systems—Subsection 3.1—the principles of functioning of self-organizing systems.
- (ii) Control in self-organizing systems—Subsection 3.2—general issues of control in self-organizing systems and features of control in digital distributed systems.
- (iii) Self-organization in manufacturing systems—Subsection 3.3—the consideration of self-organization in distributed digital production systems.
- (iv) Self-organized criticality—Subsection 3.4—the consideration of self-organized criticality and ensuring the stability of self-organizing systems, based on the study of social networks.
- (v) Modeling of self-organizing systems—Subsection 3.5—mathematical models that are used to model self-organizing systems.

3. Results and Discussion

3.1. Principles of Operating Self-Organizing Systems. The self-organizing capabilities lead to a certain set of the system's functionalities, the list of which varies slightly according to different authors. The most commonly listed functionalities are as follows:

- (i) self-monitoring;

- (ii) self-adaptation;
- (iii) self-healing;
- (iv) self-configuration.

Some papers also mention self-tuning, self-construction, self-regulation, and self-reproduction.

As artificial intelligence and process automation evolve and provide additional possibilities, the list of the functionalities of the artificial systems will also expand. However, for artificial and heterogeneous systems and their artificial elements, this does not simply mean that they would approach human capabilities. Rather, this means a better adaptation to collaborative processing of objects of various natures, as well as enabling a safe interaction [28, 29].

Self-organizing systems that exhibit nonlinear dynamics are open, nondeterministic, exist far from equilibrium, and are based on the cooperative, collective behavior of their elements. There are many publications on the properties and behavior of such systems. The fundamental principles are considered in Ref. [30]. The following features of self-organizing systems are emphasized in Ref.[31]:

- (i) *The endogenous global order*: a self-organizing system makes a transition from one stable state to another, and the final state is determined by internal processes in the system;
- (ii) *Emergence*: due to the internal interactions between the elements of a self-organizing system, the properties (functionalities) of the system as a whole are not simply a sum of the properties (functionalities) of its elements;
- (iii) *Simple local rules*: the overall complex system behavior can be based on simple (in terms of the amount of information) individual behavioral rules. Local information describes the mechanism for producing the global behavioral pattern and not the pattern itself;
- (iv) *Instability*: a small variation in the system's parameters could lead to drastic changes in the system's behavior;
- (v) *Several equilibrium states*: at the bifurcation point (when the system is unstable) there are many stable states for the system to pass to;
- (vi) *Critical state*: this characteristic is related to the presence of threshold effects or phase changes. The exit from a critical state can be carried out as a result of the internal dynamics of the system. Also, the critical state can be maintained in a stable state due to internal dynamics (SOC phenomenon).

Nonlinear dynamics is seen in several important features of such systems.

Random small deviations of the system's parameters from their average values caused by either external conditions or internal interactions may grow and lead to drastic qualitative changes in the system's behavior. In some cases, one can observe a sensitivity threshold such that small changes below it do not result in significant consequences.

It is difficult to predict the evolution and behavior of such systems based on the data for the prior intervals, because there is always a possibility of sudden changes in the pathway of processes in such systems, leading to a random and non-repeating evolutionary path in the future. At the same time, a nonlinear system might have a limited number of possible evolutionary pathways determined by its spectrum of stable states.

The openness of the self-organizing systems such as social networks implies that the existence of such systems is ensured by information exchange with the environment. The input data (for example, a new current topic) increases the structural nonhomogeneity of the system, with new groups being created and the existing ones being regrouped. At the same time, the structural nonhomogeneities are getting smaller due to information dissipation: as time passes, the entry topic gets old, and the groups of network users that were formed around it cease to exist. However, the network could evolve; a stable group or a new community could emerge, involving some of the participants interested in the development of the topic [32].

In industrial systems and e-commerce systems, which are implemented as distributed digital human-to-machine systems, the entry feed is interpreted by devices and software as well as by humans. Such systems are not always created as open systems. External information or changes in the flows of external material resources can be the cause of noise in the system. Interaction with the external environment can also be used to get out of a critical state. For example, the systems created with Industry 4.0. are often considered as working under closed internal networks (intranet) only, to secure them from any external destabilizing information. Such systems are highly ordered and organized. However, they could also lose stability due to malfunction or lack of internal resources. For example, in manufacturing, if some parts are not supplied on time or stocked ahead at the warehouse, the planned manufacture processes could be seriously affected.

Open systems can better adapt to external perturbations due to self-organization, but at the same time they present a danger of an increase in entropy, loss of stability, and emergence of chaos.

As for hybrid human-machine networked dynamical systems, it is difficult to make them completely closed even with a high level of automation, and the increase in the AI potential is itself a source of poorly predictable disturbances due to external information influx. The complexity of human interactions with the machines while they perform tasks together is yet another source of instability [33].

Self-organizing systems are based on cooperative processes. These processes differ in the equilibrium and nonequilibrium states. In the nonequilibrium state, interaction is aimed not only at achieving the main goals but also at eliminating nonequilibrium states. Recent research has paid a great deal of attention to the features of interaction as a source of fluctuations which drive the system into a nonequilibrium state, as well as to the problems of maintaining the system's stability through the rules of interaction.

For example, in Ref. [29], the following methods of lowering the chances of the emergence of contradictions in a system are considered:

- (1) *Tolerance* toward others and their goals contrary to own interests by way of internal adjustments or using additional resources to prevent conflicts and achieve common goals.
- (2) *Politeness* as modifying one's own behavior and avoiding conflicts so as not to inconvenience other parties.
- (3) *Compromise* as a combination of politeness and tolerance, when both parties have to modify their behavior to reduce conflicts.
- (4) *Imposition*, when politeness is enforced by some limitations or internal changes.
- (5) *Elimination* is a special case of the imposition strategy. An element of the system that does not contribute significantly to the system's development but causes conflicts by damaging the system's synergy can be eliminated.
- (6) *Self-elimination* is a special case of politeness when an element eliminates itself for the sake of the system as a whole.

Obviously, these methods of maintaining the stability of the processes and the system's targeted development are imminent, in the first place, to biological systems, in which the participants are capable of evaluating their actions and their impact on the system as a whole. However, these methods become equally important for digital industrial systems in which heavy machine-to-machine and human-to-machine interactions are taking place. They also serve as a basis for self-organization, especially when the devices' AI reaches higher levels.

It is noteworthy that such functions are already implemented in modern devices. For example, many devices would not begin working unless the input data are entered correctly, or would stop operation if foreign objects appear in the work area, etc.

Whereas initial research on self-organization dealt exclusively with natural systems, these days a large part of research is aimed at artificial systems. This research is motivated to a great extent by the need to find new methods and strategies for controlling such systems in order to achieve the goals important for the development of economics and the society. Such innovation becomes essential because the traditional management schemes have mostly reached their limits of efficiency.

As shown in Ref. [34], for example, self-organizing production systems (SOPS) are aimed at the realization of Flexible Manufacturing Systems (FMS) and allow one to achieve high levels of automation and a wider range of manufactured products. This paper indicates the key features of SOPS that give them advantages in comparison with traditional systems. Among these features are the flexible automation of production systems and the possibility of automated planning, which allow them to manufacture a wider array of products. The production and control systems are distributed, meaning higher stability of the system, its increased capacity to respond to unforeseen and unpredictable events, and to quickly collect and present the information on the processes in the system.

These characteristics of modern production systems are listed in Ref. [35] as a basis for a set of metrics for the evaluation of modern production systems. The following metrics are listed:

- (i) agility, which reflects the speed of response to unpredictable events;
- (ii) adaptability in the course of processing products of various levels of complexity;
- (iii) efficiency in the use of resources;
- (iv) ability to reorganize, to change the system's topology in order to create new functionalities;
- (v) self-organization, which reflects the system's ability for autonomous resolution of unforeseen internal issues.

Self-organizing networks (SON) are a separate class of self-organizing systems. Due to the automation and intellectualization of management, these networks have a dynamically changing structure; they can change and distribute functions between network nodes, for example, when a new device is connected or the traffic changes.

SON cases can be found in the sensor networks, in the mobile communications, and in transportation systems.

3.2. Control in Self-Organizing Systems. A large number of research papers on control problems in self-organizing sociotechnical distributed systems are available today. These papers deal with philosophical, social, ethical, mathematical, technological, economical, and many other aspects of such systems. In particular, there are many papers on self-organization and control in social networks. Principles and models of control in social networks are studied in detail in Ref. [36]. There are also papers that developed new concepts, for example, Refs. [37, 38].

Another direction of research deals with the applications of distributed and self-organizing systems to robotics systems and systems of intelligent agents [39–44].

Meanwhile, the functioning and stability of socio-technical networked systems that contain elements of different origin remain some of the least researched problems.

Up-to-date results on stability and loss thereof in complex networks, including online social networks, are presented in the review [45].

It provides a classification of critical phenomena arising from loss of stability in networks via various mechanisms. It also presents the mechanisms and models that describe networks in equilibrium state and critical phenomena due to loss of stability. The loss of stability in networks leads to such critical phenomena as phase transitions, which are caused by a specific external impact (the fine-tuning of a control parameter), and to self-organization into a critical state (a self-organized critical state) without any specific external impact. Even though this review was published more than 10 years ago, it still reflects the state-of-the-art knowledge in this area. The main problem is the lack of a universal model (theory) that would allow us to describe, with good enough accuracy, the mechanisms and phenomenology of the phase transitions and network transitions into the self-organized critical

state. As of today, there are a number of specialized models that describe the loss of stability during phase transitions in social networks [45–47] and during transitions into a self-organized critical state [48–50].

Among the approaches to the modeling of self-organizing distributed systems, some of the most promising are based on the models that employ the order parameter, the conjugated field and a control parameter for the description of critical phenomena.

Such an approach allows one to design methods to predict, reveal, and identify the critical phenomena, as well as to develop recommendations on how to mitigate their negative impact and ensure the system's stability.

Many authors make a point of distinguishing between natural and artificial systems [28, 51].

Digital systems are artificial; their rules are determined by the developer according to the set goals, quality criteria, and the models of the system they are meant to control. They could be further improved in the course of their operation. A possibility for the improvement of the rules follows directly from the initial definition by W. R. Ashby, who defined self-organization as a process where some form of overall order of a complex system is evolved, reproduced, or perfected [52].

Today, the most complex systems are digital industrial systems, which combine various intelligent devices, use complex distributed machining processes, and which require machine-to-machine and human-to-machine interactions for their implementation.

The papers on self-organization in industrial systems [53–61] are aimed, in the first place, at the design of such systems and realization of their control systems.

In that connection, it seems interesting that the definition of self-organization in a technological system as a process of autonomous development of the optimal structure and the optimal algorithm of its operation according to the goal the system is supposed to meet, certain quality criteria, and external conditions [62].

A control problem for a group of robots with minimal human input is described in Ref. [63]. It is concluded that to design an artificial self-organizing system to control a process or object, one needs first of all to reveal or specify a set of local rules of self-organization which will be the basis for the specific structures and algorithms, which in turn would govern the control actions.

The target goal of performing a certain series of actions under the given conditions is considered as a problem on a directed, weighted graph, with its vertices corresponding to the actions needed to solve the problem and its edges determining the precedence relationships. At the same time, each robot in the group is characterized by a certain set of actions it is able to perform.

There are also additional requirements and limitations applied to the solution. The most complicated part is to develop the sets of actions, edges, and the model of the target problem. This can be done using two approaches:

- (1) Creating the sets by the robots on their own in real time using AI methods.

- (2) Creating the sets and the model by experts as ontological models and storing them in the knowledge bases of the group's robots.

The majority of researchers distinguish the following main mechanisms of control of a self-organizing system:

- (i) Setting rules according to the goals of control so as to maintain an equilibrium in the system and making sure that those rules are followed.
- (ii) Controlling the flow of resources and limiting their use.
- (iii) Regulation of the noise level at the entrance and inside the system due to the development of the information environment, increasing the intensity of communications, and strengthening feedback. Analysis and regulation of external and internal noise allows, when adapting the system to new conditions, to make transient processes when it is necessary to change the state of the system and make its parameters smoother and more predictable.

Considering self-organization in sociotechnical systems, especially in production systems, researchers often investigate them within the framework of the concept of a System of Systems (SoS) [64–66]. SoS is composed of systems that are managerially and operationally independent.

The advantage of SoS is the ability to perform tasks that cannot be performed independently by any of its systems.

At the same time, the problem of such systems is that the potential of individual systems is not fully utilized when combining them; therefore, one of the important tasks is to ensure optimal performance through the use of various coordination mechanisms.

This approach makes it possible to increase the efficiency of distributed digital systems in many areas in which the level of autonomy of the combined systems is high, for example, in healthcare, transport, and others. This can often be observed in digital ecosystems as well, although not all authors regard them as sociotechnical systems.

3.3. Self-Organization in Manufacturing Systems. One of the groundbreaking works on the application of self-organization principles to manufacturing systems is by Kubota [67], where self-organizing manufacturing systems (SOMS) were defined.

SOMS are capable of reorganizing the hardware and software, and control in them is decentralized rather than centralized.

The main features of SOMS are generalized in Ref. [35]:

- (i) Spontaneity: they adapt to external and internal changes without an intervention from outside by adjusting and reorganizing.
- (ii) Distribution: controls are distributed among several autonomous nodes.
- (iii) Emergence: SOMS as a whole may have properties not immanent to any of its elements.

- (iv) Bottom-up method: the task arrangement is based on the solutions resulting from the communications between separate elements of the system, in contrast to making centralized solutions.
- (v) Individual autonomy: simple tasks can be solved independently by individual components of the system, while complex problems are solved through component cooperation, taking into account their autonomy.
- (vi) Self-learning: adapting to various media and self-optimization.
- (vii) Reorganization: the ability to adjust and organize its own structure and create new functionalities in response to various demands.

The complexity of modern manufacturing problems has led to the evolution of manufacturing control systems. Self-organization fits well into modern distributed models for controlling large manufacturing systems.

These models are described as systems of interacting holons (the term was coined by Arthur Koestler in Ref. [68]) and include digital agents and digital twins [69–71].

A digital twin is a specific kind of model of a physical object. A feature of this model is the presence of a constant connection between two views of an object: the physical object that really exists and a virtual one—a model that contains the information about the physical object. The two views are related throughout the life cycle of an object. In the scientific literature, the idea was first described in Ref. [72]. Grieves [73, 74] defined a digital twin as a “set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level.” Two types of digital twins are distinguished: Digital Twin Prototype (DTP) and Digital Twin Instance (DTI). DTP contains the informational sets necessary to describe and produce a physical object. DTI describes a specific corresponding physical product that an individual Digital Twin remains linked to throughout the life of that physical product. Digital twins interact in the digital environment and can be combined as Digital Twin Aggregate (DTA) for different applications. The most important is the ability to analyze the current state of objects and the system as a whole and predict future behavior and performance.

As shown in many recent papers, the basic automation model such as the standard model IEC 62264 [72], which was meant to provide centralized control, is not always efficient as a means of controlling large systems with numerous intelligent devices. Such systems are able to quickly and correctly react to the changes in the environment and adapt to them without interference from outside.

This ability is a result of digitalization of the majority of processes. It led to the evolution in control systems and the development of new decentralized concepts of the system design.

According to the basic concepts that form the foundation of the system architecture and topology, we distinguish Fractal Manufacturing Systems, Bionic Manufacturing Systems, and Holonic Manufacturing Systems [75–77].

Fractal Manufacturing Systems (FMS) are developed to make traditional manufacturing models more flexible using the ideas of self-organization and the methods that help mitigate the critical phenomena, which could result in a transition to a chaotic state.

FMS are open; their main feature is the self-similarity of their fractal units.

FMS are focused on the use of analogy with the forms of organization of natural systems in the development of a framework for the planning, design, optimization, management, and assessment of processes to supply sustainable manufacturing under environment pressure through self-organization. In the FMS, the common features of fractals are: similarity, self-organization, self-optimization, and dynamics. The organizational model assumes that all departments and even individual employees are focused on achieving business goals and are capable of entrepreneurial innovative thinking and activity. In Ref. [78], four principles of fractal sustainable manufacturing are considered: the principle of manufacturing organization fractal; the principle of organization derived from the variety or fractalinity required; the principle of fractalization of sustainable product’s life cycle; and the principle of fractal levels of sustainable manufacturing.

The concept of Bionic Manufacturing Systems (BMS) is based on the similarities between the manufacturing and biological processes, which ensure the proper functioning of all the individual parts and the entire organism by analyzing internal and external events and processes, adjusting the behavior of the organism and its components, and reproducing new elements. Ueda [79] was the first to introduce the concept of such systems based on the idea that dynamic adjustments are the result of self-growth, self-organization, adaptation, and evolution.

The basic element of BMS is called a modelon. A modelon could be composed of lower-level modelons, forming a hierarchical structure.

The information is exchanged both within and between the modelons. Similar to living organisms, the BMS possess components or mechanisms for adjustment and control which impose organizational and structural rules of interaction between modelons, so that they work toward the goals of individual processes and the common goals of the entire system [80, 81].

Holonic Manufacturing Systems (HMS) have a far higher level of self-organization than the bionic systems.

A holon’s concept states that a holon has two main parts linked to the informational and physical processes. The informational part is related to the internal communications, decision-making processes, and human-to-machine interactions, whereas the physical part is related to the control over physical processes and equipment.

A holon is autonomous; it can draw up its own plans, strategies, and oversee their implementation. It can also cooperate with other holons while following certain rules, as well as be a part of another holon.

Holons interact with each other in the course of manufacturing processes, thus forming holarchic control structures. Initially, the interaction of holons was very

limited and did not have the character of developed negotiations, although they received useful information and coordinated their actions. The expansion of the possibilities of interaction between holons is largely associated with the development of multi-agent systems in the holistic paradigm. The concept of the Holonic Multi-Agent System is based on complete decentralization of management, when management occurs only through local interactions between agents. In this case, the agent can be the entity that focused not only on solving a separate part of the general problem. It can be an integral artificial active entity capable of solving various tasks to support its existence. In Ref. [82], it is proposed to create manufacturing or functional nodes that combine a holon and a digital agent.

The agents and holons can be based on physical resources or logical objects [82]:

- (1) The functional approach: various units are used to represent functional modules in manufacturing systems; there are no direct relations between the abstract units and physical entities.
- (2) The physical approach: various units are used to represent the physical entities; there is a direct relation between the abstract units and physical entities.

The properties of a digital agent in this case must ensure the interaction between all the nodes of an intelligent manufacturing platform. A digital agent within a holon must meet the following requirements [83]:

- (i) it should be able to perceive and respond to the environment;
- (ii) it should be goal oriented;
- (iii) it should possess a large enough knowledge base to act independently;
- (iv) it should be able to interact with other agents;
- (v) it should be able to learn from prior behavior;
- (vi) it should be mobile within the network.

When implementing this model, it is important to establish the correspondence and interaction between the production holon definition and the connected agents through the mechanisms of communications, negotiations, coordination, and collaboration between various elements of the system.

The known interaction mechanisms alone cannot solve the problem in its entirety. Particular solutions are aimed at the reduction of complexity, localization of information, reduction of communication volumes, and optimization of the global behavior [84].

The following coordination mechanisms are better known:

- (i) “*Blackboard*.” There is a common area of shared information where each participant posts the information on its demands and supports, and all the parties mutually coordinate their actions according to the information on the board.

- (ii) *Market-based mechanisms* are based on auctions and contract networks: the participants list their tasks on the “market,” then the relevant parties decide if they should bid to win contracts to perform those tasks.

- (iii) *Mechanisms that model the processes in biological systems*, such as those used in BMS, are based on evolutionary processes, regulation of hormones, reinforced learning, and others.

Some other mechanisms of self-organization that could also be adapted to manufacturing control are presented in Refs. [85–87].

In human-machine systems, it is especially important to ensure error-free communication between the machine and the human, not only the communication between machines, because incorrect responses due to communication errors may often cause critical phenomena.

Digital twins play an important role in the improvement of control processes in self-organizing systems.

They model real objects or processes, and they model internal processes, technical features, and the behavior of a physical object under the action of perturbations and the environment. Digital twins not only contain current information on the state of the object, but historical data as well. This makes it possible to obtain accurate information about the system’s productivity, predict the future states, and control the object or the process remotely in real time. Digital twins of the personnel responsible for certain functions can also be used. In fact, they are replaced by avatars, which are adapted to the information exchange formats and protocols in cyber-physical systems.

The application of digital twins [88–90] reduces uncertainty and risks in the system, because when a human worker is replaced by a software agent, the worker’s functionality is better understood by digital devices interacting with them. This helps to eliminate most errors stemming from human-to-machine interactions. This makes the digital twins similar to the RPA-systems, which help reduce the number of errors by reassigning some processes from humans to automates.

Modern approaches to the SOMS implementation are reflected in the Reference Architectural Model Industry 4.0 (RAMI 4.0) [91, 92].

Technological developments ensure the improvement of the model’s components in all three of its main aspects: the architectural levels of the ICT system, the Hierarchical Levels of interconnection of the elements in the manufacturing system, and control over the Life Cycle and Value Stream.

Technologies that help combine the physical world with cyberspace and enable the structural blocks of cyber-physical systems to communicate, make decisions, and perform control are crucial for development.

Smart manufacturing equipment becomes more intelligent and autonomous. This allows us to considerably broaden the array of functions performed by machines and robots, and modify the topology of the manufacturing systems, while enhancing its capability for self-organization.

To implement a Smart Enterprise that would properly interact with the environment, it is critical to develop the concepts of a Connected World and Smart Products.

The use of the Service-Oriented Architecture (SOA) and cloud computing provides the components of a manufacturing system with the abilities to adapt and re-organize quickly, makes the entire system more flexible, and makes distributed control and self-organization possible.

The development of big data technologies and the methods of predictive and prescriptive analytics greatly enhance the possibilities and functionalities of the system's architectural layer. This is especially true when it concerns predicting and automated decision-making, which help mitigate and reduce the risks and critical phenomena due to human-to-machine interactions [93].

Research is still far from being sufficient on the application of quantum computing to the manufacturing area. Some possible applications of quantum computing in manufacturing stemming from McKinsey's predictions are given in Ref. [94]. The main tools are quantum modeling, optimization, and artificial intelligence. The improvement of yields and suppressed by-product generation through better understanding of reactions, finding new catalysts, and the use of quantum algorithms to solve complex optimization problems of heat and mass transport are given as examples of future applications.

In Ref. [95], prospects for the use of quantum computing in various fields are considered. Materials science, advanced analytics for control processes, and risk modeling are highlighted in manufacturing and industrial design. In logistics, it is possible to solve many problems of supply chain optimization, risk modeling, increasing the speed of service, easier adaptation to changes, for example, in cases of canceled orders or rescheduled deliveries. Today, the financial sector is showing considerable interest in the prospects for the use of quantum computers [96]. The great interest in quantum computing in the social sciences as a whole should be noted [97–99]. Cybersecurity is also an area that quantum computing will significantly change.

In Ref. [100], business impact of the application of quantum technologies is considered for the following areas:

- (i) material science: discovery of new candidates for drugs and materials with better properties; reduced time to market; and reduced number of real world trials;
- (ii) engineering and design: improved model and simulation quality lead to better quality; faster time-to-solution provides process efficiencies;
- (iii) production and logistics: faster and more efficient production and supply chain management; improved quality; reduced emission.

3.4. Self-Organized Criticality. The theory of self-organized criticality (SOC) has been widely used in natural sciences over the past decades.

The key notions of the general theory of phase transitions by Landau and Lifshitz [24] are the order parameter η , which

characterizes the state of the system, and the so-called Landau functional, which determines the energy associated with the spatial variation of the order parameter. Landau interpreted a phase transition as the moment when the system's symmetry changes: above the transition point, the system has a higher symmetry ($\eta > 0$, "order") than it has below the transition point ($\eta = 0$, "chaos"). Such critical states occur in a system only when there is an external impact on it; formally stated, this happens when the control parameter S reaches a certain threshold value S_C .

In Refs. [101, 102], it is noted that a critical state can occur spontaneously as a result of self-organization in the system. A classical model developed in the late 1980s by Per Bak, Chao Tang, and Kurt Wiesenfeld within the framework of the concept of self-organized criticality (SOC) (the BTW model) is a sandpile model. As sand is added, the system approaches a critical state, where addition of one more grain of sand causes an avalanche: the components of the sandpile system transition from the chaotic state to that of a regular movement. The system's order parameter (flow of sand) is slightly greater than zero, $\eta = +0$, while the control parameter S , in this case the slope of the sandpile's surface, independently reaches a certain critical value S_C regardless of the initial state. It has been proved that the size and frequency of avalanches occurring in this critical state follow the power-law distribution [103, 104]. This result, in general, is typical of critical phenomena, when a system responds to some minor event by a catastrophic change in its state.

The SOC theory was used to interpret a wide variety of phenomena in nature and society, for instance, economics [101–107], biology [108–111], earthquakes [112], political science [113, 114], sociology [115–117], brain functions (neural networks) [118–123], agriculture [124], and other fields.

Critical state in dynamic systems is one of the fundamental concepts of physical phenomena. This is a special state such that the system loses stability of a less organized (disordered) state and makes a transition to a more ordered state at the so-called bifurcation points. When the system reaches this state, a small disturbance can completely change the system's behavior. This is a classic case when quantitative changes transition into qualitative ones.

Self-organized criticality emerges in systems that possess the above self-organization functions and consist of many elements connected directly or indirectly by cause-effect relationships. This allows us to link the system's dynamics at the macro level with the behavior of its elements at the micro level, thus ensuring its integrity.

Simple events at the micro level may have consequences that affect many other events in the system over time and trigger causal waves that can superpose, thus amplifying or attenuating each other. These processes can also be resulted in the change of parameters describing the dynamics of the system at the macro level.

Chains of micro-level events lead to the appearance of the $1/f$ -pink noise and then of avalanches. At the same time, the system can stay in a critical state relatively long if stability is enforced one way or another.

The classic BTW model with its many versions as well as other models can be considered as cellular automata. Other

approaches used in the modeling of self-organization include multi-agent systems, evolutionary computing, neural networks, and hybrid intelligent systems.

The following models are used most frequently:

- (i) Stick-slip model of fault failure [125];
- (ii) Forest-fire model [126, 127];
- (iii) Olami-Feder-Christensen's model, an earthquake model [112, 128].
- (iv) Bak-Sneppen's model, BS-model, co-evolution model [129].

The examples of physical processes with SOC behavior are given in Ref. [130], where one can find those used as a metaphor for the developed models, as well as those used in the models of interaction in the digital environment, for example, traffic collisions, stock market crash, or a lottery win.

Very often SOC effects are observed in the agent-oriented models [131].

A large number of studies deal with the applications of the SOC theory for the simulation of the information propagation on the Internet, in particular, in social networks [48, 49, 132, 133].

In the community of users of a social network, a random message that is not interesting to other users and not retransmitted by them does not lead to a change in the state of the network. If, on the other hand, a message is retransmitted by a critical number of active users of the social network, it quickly becomes popular, and at some point this can lead to a system-wide transition to a critical state, which is characterized by a spontaneous increase in user activity and an avalanche of messages. The situation described above is very well in line with the concept of a self-organized critical system. Indeed, SOC-based models have been successfully used in studies of various phenomena observed not only in social networks but also in social and sociotechnical systems.

For example, in Ref. [133], empirical data and agent modeling are used to analyze the phenomenon of collective emotional behavior of users which is often observed on various web portals. The emphasis is on the quantitative evaluation of the collective emotions through fractal analysis of the underlying self-organizing dynamic processes, as well as the topology of the social networks which occur and coherently develop in these stochastic processes.

Initially, fractal market analysis was introduced by Mandelbrot and Hudson [134]. Fractal analysis is now widely used in all areas of science.

Fractal analysis consists of several methods to assign a fractal dimension and other fractal characteristics to a dataset. Fractal analysis is valuable in expanding our knowledge of the structure and function of various systems. Refs. [135, 136] discuss the use of fractal analysis of social networks.

Data from the Twitter social network are used in Ref. [132] to study fluctuations in the frequency of brand tweets. The frequency of tweets is an outcome of strongly correlated user behavior, which leads to turbulent collective dynamics

with the characteristic $1/f$ noise. An integral parameter measuring the user's interest in a brand is used to simulate the collective human dynamics using a stochastic differential equation with multiplicative noise. The model is supported by a detailed analysis of the fluctuations in the rate of tweets; it reproduces both the exact dynamics of peaks and the $1/f$ noise.

From the point of view of the complexity paradigm, a microblogging social network can be described as a non-linear, nonequilibrium dynamic system in a three-dimensional phase space. The flows of messages (posts) in microblogging networks are prone to the emergence of critical states, i.e., avalanches of messages. Analysis of the time series for these messages reveals several features of a classical SOC model: power-law statistics of the probability distribution, $1/f$ flicker noise of the power spectral density of the time series, and the presence of events that can be viewed as catastrophic [137–141].

The Twitter network is considered in Refs. [142, 143] using the SOC model, because Twitter is prone to avalanche-like message streams, from tens to thousands of posts per second. It is hypothesized that Twitter's self-organization in a critical condition is the result of a special persistent ("strategic") behavior of a relatively small number of users.

All Twitter users can be tentatively divided into two groups: a small number of strategically oriented users (SOUs), and the majority of randomly oriented users (ROUs). The basic state of the network, when messages are generated by ROUs, corresponds to a chaotic state in a classical dynamical system, since these messages are not connected to each other and quickly disappear from the user's horizon. The critical state occurs when the number of coherent SOUs messages aimed at the same outcome reaches a certain critical value, such that yet one more SOU causes the network to transition into an ordered state and creates an avalanche of messages.

Similar ideas were also voiced by other authors. For example, it is suggested in Ref. [144] that each social network has "influence agents," i.e., users holding certain key positions in the network, which gains them a strong structural ability to influence the entire population of users. The activity of influencers more often than the activity of other network users can lead to the emergence of critical states characterized by macroscopic effects.

Arguably, the social microblogging networks develop holistic properties immanent to complex systems. This conclusion is supported by a power-law dependence of the autocorrelation function for the messages time series. This means that the current number of messages depends mostly on the number of messages generated in the social network in the past. Here, we see a manifestation of the characteristic ability of SOC systems to possess a long time memory [145].

It is noted in Ref. [146] that, when a social network's dynamics is based on human effort, it is difficult for it to acquire new features such as collective social values. The vast amount of empirical data collected from various websites provides a unique opportunity to quantify social dynamics the same way this is done for complex physical systems. It is suggested that the dynamics of social knowledge exchange is

governed by the SOC mechanism; moreover, the emergence of hyperbolic geometry in such social systems was demonstrated.

It is noteworthy that self-organized systems do not always exhibit the properties of criticality. Research and differentiation between the SOC, SOC-like, and non-SOC processes was done in Ref. [130]. Based on the proposed metrics, the difference between various SOC or SOC-like processes was studied such as The Exponential-Growth model (EG-SOC), Fractal-Diffusive model (FD-SOC), Forced Self-Organized Criticality model (FSOC), Self-Organization Without Criticality (SO), Brownian Motion and Classical Diffusion, Hyper-Diffusion (thresholded), Levy Flight (thresholded), Nonextensive Tsallis Entropy, and Turbulence (laminar/turbulent). Power law of spatial scales, power law of time scales, power law of total energy, power law of energy dissipation rate, fractal geometry, intermittency in time evolution, statistical independence of events, critical threshold restoration, next-neighbor interaction, and nonlocal (long-range) coupling were used as metrics to quantify the system's properties.

An important result of Ref. [130] is the differences shown to exist between SO and SOC in terms of stability of the system states. Self-organization can be characterized by rather long intervals of stability of the emerging landscape of more or less stable areas of the entire system. This relative stability is regulated via long-term interactions through rules, pressure, and forces. SOC generates dynamic events (avalanches) when intermittent avalanches occur due to random-like disturbances.

One of the most important tasks for digital distributed systems, which have applications in various fields, is to ensure their stability.

Stability is the ability of a system to function without changing its own structure and to be in balance. A system is said to be stable if it does not exhibit large changes in its output for a small change in its input, initial conditions, or its system parameters. In a stable system, the output is predictable and finite for a given input.

An understanding of the minimally stable state is essential also in understanding the self-organized critical state [102].

In Ref. [147], it is noted that there is a class of complex systems with a large number of degrees of freedom that enter a critical mode by their very nature, as a result of the internal tendencies of evolution inherent in these systems. Critical states of such systems do not require precise adjustment of external control parameters and in fact have the property of self-support.

For real sociotechnical systems, it is important to detect and analyze critical phenomena and assess the state of the system in order to, if necessary, improve it in time, ensuring stable functioning.

A sociotechnical digital distributed system is a complex network structure. As shown in Ref. [147] "critical phenomena in network structures include a wide range (forms of behavior) of phenomena: structural changes in networks, the emergence of a critical state, various percolation phenomena, critical points in various optimization problems,

and many others. Many of these critical phenomena are closely related, have a similar nature, and allow for a universal description."

Critical phenomena in such systems are primarily connected with the risk of loss of control and disintegration of the system. Since in such digital systems, especially manufacturing systems, the processes involve both equipment and people, critical phenomena may endanger not only the manufacturing processes but also people's health and lives, as well as the environment (sometimes, the criticality could instead allow the unlocking of situations otherwise blocked, or in deadlock). Hence, it is extremely important to study the critical phenomena and the methods of their prevention.

The problems of control of nondeterministic dynamics in self-organizing systems, an optimal balance between external impact that adversely affects the reliability, adaptability, and scalability of the system on the one hand, and the amount of uncertainty, which could make the verification and validation of the system an impossible task, on the other hand, are discussed in Refs. [148–152]. It is shown that finding such a balance helps solve various practical problems, for example, in traffic control [149], design of robotic teams [150], data visualization [151], development of services in Grid networks [152], and many others.

Many studies explore the methods and principles of making decentralized decisions in multi-agent systems [86, 153–158].

Cyber-physical and cyber-social systems are becoming more complex, and at the same time, the number of different approaches to modeling of those systems in the context of self-organization is growing.

Special issue [159] discusses an increase in the complexity of digital sociotechnical systems, including social media, the Internet of Things, RPA systems, digital business platforms, algorithmic decision-making, digital networks, and ecosystems.

Phase transitions in business processes supported by digital technologies are simulated in Ref. [160]. Gradual endogenous changes in the system may lead to a state of self-organizing criticality. As the process approaches this state, further incremental changes may result in nonlinear surges in the process complexity and significant modifications of its structure.

The review [161] examines the simulation of complex dynamic network structures where interactions occur within groups of three or more nodes. It is noted that such models correspond well to the architecture of real complex systems. Taking into account the higher-order structures in those systems could widen the scope of simulations and help with understanding and predicting the system's dynamic behavior. This could also help to provide an adequate description of the state of self-organizing criticality that is typical of many similar systems.

To characterize the stability of a self-organizing system, it is important to quantify the level of self-organization, since a tendency of gradual degradation of self-organization and transition to hierarchical control can occur in sociotechnical systems. On the other hand, technical systems may gradually

evolve toward self-organized criticality. A definition of quasi-stationary self-organization systems, when the system parameters vary much slower than typical dynamical motions in the system, is given in Ref. [162]. Self-organization in complex systems is regarded as a process of human decision-making, and vice versa; the decision-making is considered as self-organization in the nervous system of those who make decisions. A similarity between those processes is also demonstrated in a number of other publications, for example, in Ref. [163].

A number of studies present approaches that make it possible to quantify the state of self-organization in a system. The characteristics of structures, patterns, scenarios, or prospects are associated with specific states.

Several well-known metrics for quantification of self-organization are considered, such as the Shannon entropy [164], the von Foerster redundancy [165, 166] and some others, as well as the new approach proposed by the authors and based on the methods of the quantum theory of measurement [167, 168] and quantum information theory [169, 170].

The interest in self-organization as a process similar to the decision-making process reflects several important trends related to the development of digitization and digital systems in various fields. Those trends include progress in the intelligence and autonomy of equipment and robots, an increase in the rate of information exchange and the volume of information traffic, and an ever greater degree of process automation. Given all that, it is likely that a better understanding of theories and practices of decision-making in human communities, and subsequent application of them to digital systems, could help achieve a greater stability in self-organizing heterogeneous systems.

3.5. Modeling of Self-Organizing Systems. Mathematical modeling of sociotechnical networked self-organizing systems is a nontrivial task, because, as was shown above, they necessitate joint participation of and interactions between humans and miscellaneous digital equipment, including intelligent tools.

Modern digitalization capabilities allow for an agent-centric approach to these systems which combines the physical or functional elements of the systems with the agents that ensure the communications.

An overview of various methods of modeling self-organizing systems is presented in Ref. [171]. Modeling at the micro level can be used to describe the behavior of each element of the system as well as the communication between the elements. It has an advantage of providing a more detailed description of the real system, but the downside is a high dimensionality of the model's global state space. At the macro level, models do not deal with individual entities of the system and consider their equivalence classes instead, thus reducing the vast micro-level state space. At the micro level, the properties of the models of sociotechnical distributed systems discussed here (time, space, etc.) are conceptually discrete in nature, while, as a rule, synchronous time renewal is used, while at the macro level these properties are continuous.

Thus, two main approaches can be distinguished in mathematical modeling of digital distributed systems:

- (a) discrete *ad hoc* models;
- (b) discrete models based on the ideas borrowed from mathematical modeling in biology;
- (c) continuous models using analogs from biology, mechanics, etc.

Among them, the most widely used approach relies on discrete modeling [172–180].

That is hardly surprising: a relatively small number of agents in the system allows us to formalize and numerically describe the interaction mechanisms between specific agents. On the other hand, this is exactly what makes a transition to “continuous models” difficult.

However, when modeling social networks with a huge number of actors (for example, the number of Twitter microblogging users exceeds 300 million), it becomes almost impossible to take into account the individual properties of each actor; therefore, in this situation, along with discrete modeling [181–185], an approach based on the use of systems of ordinary differential equations is used. The independent variable in such models is time; dependent are various quantitative characteristics that describe the number of tweets, retweets, etc.

Some discrete models are developed *ad hoc* [172–177], but more often, well-known models from biology based on the genetic algorithm or models of some aspects of the insect behavior (bees, ants) [179, 180] are used as a foundation for discrete models.

Continuous models [181–184] also often use analogs from biology and from hydrodynamics.

Considering particular models of digital distributed systems, we can evaluate the applicability of these approaches to specific systems.

3.5.1. Discrete Ad Hoc Models. A general method of analysis of multi-agent systems, which allows us to define strategies for local interactions by specifying a preferred global behavior of the system, and then to evaluate possible strategies using Markov analysis, is proposed in Ref. [172]. The choice of cooperation strategies is based on the iterative application of the “prisoner’s dilemma.” As shown, it is similar to the “tit for tat with forgiveness” strategy, which, under certain circumstances, surpasses the well-known “tit for tat” strategy. The latter is used, for example, in the peer-to-peer file-sharing network BitTorrent.

- (1) A distributed, service-oriented, multi-agent system where the agents must communicate with each other to perform decentralized tasks of service discovery is considered in Ref. [173]. Since the system’s structure may affect the efficiency of the service discovery, a structural self-organization mechanism should be used to facilitate the decentralized discovery.

During the discovery of decentralized services, different agents will present different intermediate utilities, and those utilities imply, to a certain degree, information about the distribution of the system's services. Hence, an intermediate utility can be used to improve the efficiency of both structural self-organization and the search for services. Moreover, the availability of global services is ensured by maintaining the global connectivity of the system's structure during parallel self-organizational processes.

A *system* is defined as a pair $\langle A, L \rangle$, where $A = \{i, \dots, n\}$ is a set of agents, and $L \subseteq A \times A$ is a set of relationships between the agents; each relationship indicates a symmetric interaction between agents i and j .

Agent-to-agent relationships have a locked flag:

$L(i, j)$ indicates a locked relationship between i and j ;

$L(i, j)$ indicates an unlocked relationship between i and j .

If a relationship becomes locked, it means that one of the agents intends to break it.

If a request for service is successful, the agent i is considering changing its relationships. If the following holds:

$$\max_{k \in A_i^K} \{\eta_{ik}\} > \min_{j \in A_i^N \wedge L(i,j)} \{SV_{ij}\} + \gamma, \quad (1)$$

where η_{ik} is an estimate of the potential weight (cost of creating a relationship) for the acquaintances $k \in A_i^K$ of agent i ; SV_{ij} is the system value of the relationship between agents i and j , under the condition $SV_{ij} = \max\{\tau_{ij}, \tau_{ji}\}$; and τ_{ij} is an estimate of the weight for the neighbors j of agent i ; $\gamma (\gamma > 0)$ is a constant.

In this case, it is possible to improve the quality of communication set of the agent by structural self-organization as follows:

- (1) Agent i sends a message to agent j with the minimum SV_{ij} a message about blocking the communication (i, j) ; if agent j has already blocked the communication, it will respond with a denial; otherwise, it will send back a confirmation;
- (2) If agent i receives a denial, it does nothing; if agent i receives a confirmation, a new type of request AQ is generated to find the appropriate agent to form the relationship $AQ = (i, j, DI, TTL', k, A_v' = \{i\})$, where i and j are the above agents' numbers; DI is the demand information; TTL' is the maximum number of requests forwards; k is the number of the acquaintance with the largest η_{ik} ; and A_v' is the set of agents that received the request in the course of forwarding.
- (3) If $TTL' < 0$, the request is sent back to i . Otherwise, if $TTL' \geq 0$, then agent m decrements

TTL' in the query by 1 and, if $m \notin A_v'$, includes itself in A_v' ;

- (4) The request is forwarded to agent m^* :

$$m^* = \begin{cases} \operatorname{argmax}_{n \in L(A_m^N) \wedge n \notin A_v'} \{\eta_{in}\} & \text{if } L(A_m^N) - A_v' \neq \emptyset, \\ \operatorname{precursor}(m) & \text{otherwise.} \end{cases} \quad (2)$$

Here, based on empirical estimates, it is assumed that $TTL' = 10$, $\gamma = 0.1$.

Compared to a number of known approaches (*simplicity-based search without structural adaptation, simplicity-based search with deterministic structural adaptation based on service property, simplicity-based search with probabilistic structural adaptation based on a decay function*), this model increases the efficiency and reduces the time needed for the system to come to a stable state, especially when it is adapting to varying content of the search queries.

- (2) Two mechanisms of self-organization for a decentralized service discovery system that improve its performance are described in Ref. [174]. These mechanisms are based on local activities of agents, which only consider local information about the requests that they forward during the discovery process.

The following self-organization activities are noted: staying logged in, logging out, cloning, and changing the structural relationships with other agents. Each agent independently picks the actions it deems appropriate.

A *system* is defined as a Service Oriented Multi-Agent System (SOMAS): $\langle A, L \rangle$, where $A = \{i, \dots, n\}$ is a set of agents, and $L \subseteq A \times A$ is a set of connections between them; each connection $(i, j) \in L$ indicates the presence of a symmetric interaction between agents i and j .

The function of the search for the most promising neighbor is defined as follows:

$$\mathcal{F}_N(t) = \operatorname{argmax}_{j \in N_i} \left[1 - \left(1 - \left(\frac{CH(j, t)}{\sum_{n \in N_i} CH(n, t)} \right) \right)^{|N_j|} \right]. \quad (3)$$

Here $t = (r_q, s_q, \emptyset, \emptyset)$ is a fake agent representing an unknown agent-provider of the requested service (or similar to it); CH is the Choice Homophily, which evaluates the proximity of agent-neighbor j to the fictitious agent i :

The function of selection of the local action of self-organization is defined as follows:

$$\mathcal{F}_A: st_i \longrightarrow \psi. \quad (4)$$

Here $\psi = (\text{clone, remain, leave, rewire})$ is a set of possible actions. Structural self-organization of agents follows CH .

The mechanism of structural self-organization promotes a decentralized discovery of the services in the system. The algorithm that supports the mechanism of self-organization consists of the following stages:

- (i) the agents search for services;
- (ii) the agents verify whether the local information is complete and reliable;
- (iii) the agents decide whether to maintain, strengthen, or create new structural relationships;
- (iv) the agents decide whether to stay logged in, log out, or get cloned.

Discrete models are sometimes used to analyze the behavior of the users of social networks (when the test data volume is relatively small). The model proposed in Ref. [175] can be used to integrate multiple social networks, import and process data by means of the modern big data technologies. This model allows one to record the activities of Internet users taking into account the combination of human and temporal factors, as well as to reveal both positive and negative trends in the evolution of opinions formed by network users.

Agents (Internet users) are represented by u_i , where $i = 1, \dots, N_u$ is the number of users. The information exchange between users is expressed via posts, messages, or comments p_j , $j = 1, \dots, N_w$.

Thus, a message is generated as an event of the following type:

$$g_{i,j} = (u_i, p_j, t_{i,j}^0), \quad (5)$$

where t is the time of the message generation.

The process of the message sending or processing is represented by event $e_{i,j}$. This is a logical variable that depends, among others, on the focus, i.e., the current scope of interest of the user; the focus is described by a cloud of weighted tags (keywords). Each user has his or her own ontology, which determines the basis of their perception (messages). It changes over time as a result of the process of remembering and forgetting the information received from messages. The ontology is represented by a sequence of contexts defined by tags. Changes in focus and context correlate with each other; their correlation is described by a logical variable. Therefore, the generation or processing of a message does not guarantee changes in focus and context.

The software that identifies the focus of social media is based on the knowledge search and big data analysis, which can also help to elucidate the impact of online bots.

In some cases, discrete models can be self-learning. In particular, there is a discussion in Ref. [176] of self-organization mechanisms that can build, in an automatic, flexible, decentralized manner, services for adapting the agents' local behavior and the structural relations between them.

The model defines the following roles of the agents: *consumer*, *supplier*, *work process*, *ontology*, and *reputation*.

The model employs an approach based on decentralization. To that end, dynamic communities of service-oriented agents are created, and requests are directed to those communities. By automatically creating new connections, a useful agent can seamlessly join a community. The community, on the other hand, is able to break connections with useless agents.

A novel self-learning mechanism, which allows distributed objects to change their structural relations and thus enable the system's evolution, is organized as follows. An agent makes decisions based both on its current state and on the quality of a potential reward for performing an action in that state. The reward is based on the agent's status, action, and feedback. The calculation of the reward is done in two stages: first, the reward is evaluated qualitatively, then it is converted into a numerical equivalent. If the system's evolution is stable, i.e., this process converges, then the agent is considering the possibility of creating new structural connections.

This approach improves the quality of service and reduces the network traffic.

3.5.2. Discrete Models Based on the Ideas of Mathematical Modeling of Biological Systems. The genetic algorithm is one of the traditional approaches. It is applied in Ref. [177] to mobile *ad hoc* networks (MANET), which are widely used in various situations, from military to business tasks, including disaster zone detection, mine field clearance, and transportation systems.

In real-world environments, it often does not make sense to deploy network nodes manually or using a centralized controller. To achieve self-organization of mobile nodes in an unknown area, the following nature-inspired approach is the most promising: each mobile node (agent) uses *the genetic algorithm* as a *self-propagation* mechanism. This allows it to determine its own speed and direction and ultimately to evenly distribute all network nodes.

Each agent (node) is characterized by a set of chromosomes of the following type: $\langle d_1, d_2, d_3, s_1, s_2 \rangle$, where d_1, d_2, d_3 are the direction bits, and s_1, s_2 are the speed bits.

Let us consider two nodes N_i and N_j . The force of attraction F_{ij} between the nodes N_i and N_j is expressed as follows:

$$F_{ij} = \begin{cases} F_{\max}, & \text{if } d_{ij} = 0, \\ \sigma_i(d_{th} - d_{ij}), & \text{if } 0 < d_{ij} < d_{th}, \\ 0, & \text{if } d_{th} \leq d_{ij} \leq R_{\text{com}}, \end{cases} \quad (6)$$

where d_{ij} is the Euclidean distance between nodes N_i and N_j ; d_{th} is the radius within which the agents can be considered to be neighbors; σ_i is the expected degree of node N_i (a function of the average degree of nodes on the network and the number of N_i neighbors); R_{com} is the (maximum) communication radius of the node.

For the node N_i with k neighbors, the fitness value is defined as follows:

$$\text{minimize: } \sum_{j=1}^k F_{ij} = \sum_{j=1}^k \sigma_i(d_{th} - d_{ij}), \quad \text{for } 0 < d_{ij} \leq d_{th}, \quad (7)$$

subject to: $d_{\text{mov}} \leq d_{\text{max}}$,

where d_{mov} is the distance covered by the node based on the information in the chromosome; d_{max} is the maximum distance allowed.

The system's evolution is modeled by a nonhomogeneous Markov chain defined by its transition matrix (x_{kl}). Its elements are the probabilities of the node's transition from state k to state l at each step of the Markov chain; $k, l = 1, 2, \dots, n$.

This approach demonstrates the evolution of a self-organizing system, which leads to an almost uniform distribution of nodes (agents) over the area.

To simulate dynamic interactions between Web services and solve some of the problems associated with their composition and adaptation, a stigma-based approach (a mechanism of spontaneous indirect interactions between individuals, when they leave tags in the operation domain to stimulate further activity of other individuals) is proposed in Ref. [178]. The proposed approach treats Web services and resources as sets of agents. The stigma-based self-organization of agents is used to develop and adapt compositions of Web services.

A service agent is defined as a pair $p_i = \langle id, F \rangle$, where id is the agent's identifier and F is the pheromone store, $F = \{f_1, f_2, \dots, f_n\}$. Each fragrance contains a scalar value that represents the trajectory of a particular service agent. The quantity (volume) of a pheromone released and/or accepted by an agent is denoted by Q_{f_i} . Based on the user requests, service agent p_i requests an abstract work process, $r_j = \{r_{j1}, r_{j2}, \dots, r_{jn}\}$, where r_{ji} is a specific service or resource that must be compiled to perform a single subtask. Thus, the requesting agent sends search queries through a local subnet of the associated agents to generate r_j . The operations of aggregation, evaporation, and storage of pheromones are introduced. Equations that determine the strength of smell f_i for agent p_i at time t and the sum of the amounts of pheromone f_i transferred to agent p_i at time t are given.

This approach enables self-organization even if one deals with incomplete (local) information and dynamic factors in a decentralized environment.

So-Grid, a set of bio-inspired algorithms adapted to the decentralized construction of the Grid information system, which is both adaptive and capable of self-organization, is presented in Ref. [179]. Such algorithms use the properties of swarm systems, where a number of entities (agents) perform simple operations on the local level, but together they produce an expanded form of swarm intelligence on the global level.

In particular, So-Grid provides two main functions: a logical rearrangement of resources, similar to the behavior of some ant and termite species, which move and collect objects from their environment, and a resource

search similar to the mechanisms ants use to search for food.

In the Grid environment, a number of agents move autonomously like ants across the Grid through P2P connections and use skewed probability functions to: (i) replicate the resource descriptors, thereby facilitating resource discovery; (ii) collect similar resource descriptors in adjacent Grid hosts; (iii) promote distribution of the descriptors corresponding to fresh (recently updated) resources, as well as resources with high Quality of Service (QoS) characteristics.

The proposed approach is characterized by self-organization, scalability, and adaptability, making it useful for dynamic and partially unreliable distributed systems.

The So-Grid replication algorithm can reduce the system's entropy and efficiently distribute the content (information). Moreover, since the descriptors get gradually reorganized and replicated, the So-Grid discovery algorithm allows users to more quickly reach the Grid hosts that store information about more useful resources.

The model [180] based on the "honeybee" agents enables the discovery of cloud services on several levels.

The implementation of the proposed approach involves the following three phases:

- (i) the development of a search model for a "hired collector bee" agent to discover private and dedicated cloud resources;
- (ii) the deployment of a "scout bee" agent based on the mechanism of detecting unknown cloud sources;
- (iii) the knowledge incurred through "waggle dancing mechanism." The onlooker bee agents will find unknown cloud sources, and the collected resources are clustered by resource cluster methods.

The "honeybee" agents are cooperative and can be efficiently used for search automation and grouping of cloud services.

The proposed solution greatly simplifies the search process: instead of spending a lot of time and effort discovering, evaluating, and exploring cloud clusters, users can easily discover, select, and use the services they need. In addition, cloud service providers (CSPs) can publish targeted information about their services.

3.5.3. Continuous Models Using Analogies from the Population Dynamics. The design of a synergistic system for managing self-organizing virtual communities, in particular, social networking services (SNS), enables the transition from chaos to a controlled process, thus achieving predictable results for the interaction between their agents. Several models that confirm this behavior of the systems are presented in Ref. [181].

A model of SNS can be expressed as follows:

$$\begin{cases} \frac{dx_i(t)}{dt} = f_i(x_1(t), \dots, x_\lambda(t), y_{\lambda+1}(t), \dots, y_\mu(t)), \\ \frac{dy_j(t)}{dt} = f_j(x_1(t), \dots, x_\lambda(t), y_{\lambda+1}(t), \dots, y_\mu(t), u_1(t), \dots, u_\gamma(t)), \end{cases} \quad (8)$$

$$x_i(t_0) = x_i^0, \quad y_j(t_0) = y_j^0,$$

$$x_1(t) = T(t) - T_0, \quad (13)$$

is the deviation from the number of tweets T_0 in the state of stable equilibrium;

$$x_2(t) = R(t) - R_0, \quad (14)$$

is a similar expression for retweets.

The rates of change of the variables can be written down in a parametric form, yielding a system of equations similar to the population dynamics equations:

$$\begin{cases} \dot{x}_1(t) = -\alpha x_1(t) + \beta x_2(t), \\ \dot{x}_2(t) = -\gamma x_1(t) + c x_2(t) x_3(t), \\ \dot{x}_3(t) = \varepsilon (I_0 - N(t)) - k x_1(t) k x_2(t). \end{cases} \quad (15)$$

It is shown that the above system is reduced to the well-known Lorentz dynamic system:

$$\begin{cases} \dot{x} = \sigma(y - x), \\ \dot{y} = -y + xz, \\ \dot{z} = b(\rho - z) - xy. \end{cases} \quad (16)$$

This system has an attractor. The nonequilibrium dynamics of the system exhibits a singularity and a multiplexing character. A numerical experiment conducted on real-world data from the Twitter microblogging network showed that Twitter's dynamics is more often chaotic than regular.

Different levels of description of the dynamics for a large group of agents influenced by a small number of external agents are presented in Ref. [183]. The microscopic dynamics is described via classical flocking models supplemented by a metric on a set of agents and by a rule of their topological interaction. The mesoscopic description is obtained using the mean-field limit and is a hybrid model of a single kinetic equation for the system of agents and a system of ordinary differential equations that control the external agents. Finally, the macroscopic level is modeled using an appropriate system of equations of fluid dynamics. A similar approach to modeling of multi-agent social systems with the help of fluid dynamics analogies is also presented in Ref. [184].

An idea that self-organization in complex systems can be seen as a decision-making process similar to human decision-making and, vice versa, the decision-making process is nothing more than a kind of self-organization of the nervous system of those who make decisions, is presented in Ref. [162]. Similarities between these processes are also shown in a number of other works, for example, Ref. [163].

where $x_i(t)$, $y_j(t)$ are the indicators of agent interaction, $i = 1, 2, \dots, \lambda$, $j = \lambda + 1, \lambda + 2, \dots, \mu$;

$u_l(t)$ $l = 1, 2, \dots, \gamma$ stands for SNS control feedback; $x_i(t_0) = x_i^0$, $y_j(t_0) = y_j^0$, are the initial conditions.

The macro variable $\psi_v(x_i, y_j) = 0$, $v = 1, 2, \dots$, is the parameter that determines the dynamics of interaction between the SNS agents. It ensures that the system is self-organized.

$$\psi_v = \psi_k(x_1, y_1, \dots, x_\lambda, y_\mu) + \psi_d(x_1, y_1, \dots, x_\lambda, y_\mu), \quad (9)$$

where $\psi_k(x_1, y_1, \dots, x_\lambda, y_\mu)$ is the conservative component of the system, $k = 1, 2, \dots$; $\psi_d(x_1, y_1, \dots, x_\lambda, y_\mu)$ is the dissipative component in the system, $d = 1, 2, \dots$.

The designed system state in the phase space shall be a point called a synergy splash point. However, its trajectory in the phase space must correspond to the following equation:

$$T_v \frac{d\psi_v(t)}{dt} + \psi_v(t) = 0, \quad (10)$$

where T_v is the period of all transitions initiated by the SNS Actors' Interaction Synergetic Control.

To simulate a specific situation, the model was defined as follows:

$$\begin{cases} \frac{dx(t)}{dt} = ax - xy - bx^2; \\ \frac{dy(t)}{dt} = -cy + xy, \end{cases} \quad (11)$$

where $x(t)$ stands for the process describing SNS actors' market for the information attractive to the virtual community investigated; $y(t)$ describes the attractive information supply; a indicates SNS actors' demand shift rate for attractive information, should $a > 0$ demand increase, should $a < 0$ demand decrease; b indicates SNS actors' rivalry in response to the substantially identical information posted; c indicates supply shift rate for information attractive to SNS actors.

The system may be in a certain stable condition called an attractor, which, however, is negatively affected by a potential threat to social media subjects.

A model of a social network of microblogs is given in Ref. [182], where the network is considered as a point-dissipative system describing the behavior of the following parameters, where

$$x_3(t) = N^*(t) - N_0(t), \quad (12)$$

is the difference between the number of network users who are in the excited and in the base states at time t ;

The mathematical formulation of the above approach is based on the probabilities of the system's states, i.e., the probabilities of its structures, models, evolutionary scenarios, etc. It is shown that the mathematical formalisms of self-organization and decision-making processes are identical. Thus, self-organization can be considered as an endogenous decision-making process, and, accordingly, the decision-making takes place through endogenous self-organization.

The proposed approach is illustrated by phase transitions in large statistical systems, evolutions and revolutions in social and biological systems, structural self-organization in dynamical systems, and probabilistic formulations in the classical and behavioral decision-making theories. In general, self-organization in these cases is described as a process of estimation of the probabilities of macroscopic states, or as a search for the most probable state. Application of the principle of minimal information is the standard way to obtain a probabilistic measure in classical systems. In other words, one needs to perform the conditional maximization of entropy under given constraints. Possible behavioral bias of decision-makers can be considered the same way that quantum fluctuations are treated in physical systems.

In applications to social systems, one uses a constraint called a systemic frustration or conflict, which is equivalent to the energy of a physical system. We can define an analogy of the free energy in social systems in the following way. The energy of system $E(\pi_j)$ in state j shall be called the state cost. The noise intensity T is an equivalent of the temperature of a social system, whereas the environment that generates the noise plays the role of a thermostat. The noise energy or noise cost for the system in state π_j is expressed by $TS(\pi_j)$, where $S(\pi_j)$ is the entropy of state π_j . Then, the equivalent of the free energy – the free cost – is the intrinsic state cost, i.e., the state cost less the noise cost:

$$F(\pi_j) = E(\pi_j) - TS(\pi_j). \quad (17)$$

Since the system is finite, the set of agents cannot exist in a single pure state, but rather it is characterized by probabilities of being in different states. Therefore, the probabilities obey the following distribution:

$$p(\pi_j) = \frac{1}{Z} \exp\{-\beta \cdot F(\pi_j)\}. \quad (18)$$

with the partition function

$$Z = \sum_j \exp\{-\beta \cdot F(\pi_j)\}, \quad (19)$$

where β is a Lagrange multiplier corresponding to the inverse temperature, $T=1/\beta$.

Phase transitions occur between the dominant states, with continuous transitions corresponding to evolution, and discontinuous ones to revolutions or abrupt mode changes.

The above review highlights the following conclusions regarding the application of different model classes:

- (i) The approach based on systems of ordinary differential equations is only meaningful when the system consists of a very large number of homogeneous actors (e.g., social networks). When the system consists of a relatively small number of actors with different roles and forms of interaction, discrete models are more appropriate.
- (ii) In discrete models, the most difficult problem is to adequately describe the connections and interactions between actors. Sometimes such formalism is created ad hoc, requiring, as a rule, the development of original and sophisticated mathematical methods.
- (iii) Another common approach involves the application of known biological models (the genetic algorithm or models for the behavior of colonies of insects such as bees or ants), where a well-developed mathematical formalism is available. However, it often requires the problem at hand to be adapted to fit the model, which can lead to the loss of important properties of the simulated system.

4. Conclusions

As shown in this review, self-organization is essential for the functioning of networked dynamical sociotechnical systems. The reasons are their high complexity and diversity, the complexity and increasing intelligence of their digital elements, and their distributed digital infrastructure. Moreover, self-organization becomes necessary when a system to be designed has to meet such criteria as high flexibility and process adaptability, active communication in the course of the processes of decision-making, operational tune-up, and system topology adjustments. Such tasks and objectives make centralized control inefficient and sometimes impossible under the imposed constraints.

In sociotechnical systems, a collaboration between humans and equipment is required even when the processes are digitized to a great extent. At the same time, two tendencies make those two groups of the systems' elements closer: the equipment becomes more intelligent, being developed toward modeling and reproduction of the human psyche. On the other hand, people are replaced by intelligent agents or digital twins that emulate human functionality and decision-making methods, and communicate on their behalf.

In this case, all the elements of the system become digital; however, as a rule, a human is still involved in monitoring, control, and decision-making. The development of big data technologies and communication networks makes it possible to bring social and technical entities closer together, thus enhancing the human ability to receive and analyze information, automate the decision-making processes, and interact with the equipment directly or remotely. As for the equipment, now it can learn to independently monitor, test, restore, and

configure the system processes. Thus, a conclusion made in Ref. [164] that self-organization can be considered as an endogenous decision-making process, and consequently, that decision-making takes place through endogenous self-organization, is clearly confirmed by practice. In the future, we can expect the scope of applications of the methods used to support decision-making in the models of digital distributed systems to expand even further.

The review focuses on two types of networked dynamical self-organizing sociotechnical systems, namely, manufacturing systems and social networks. In today's digital manufacturing systems, the hardware component dominates in most cases, while in social networks, despite their advanced digital infrastructure, the social component dominates, although a bot, an agent, or a digital twin might act on behalf of a particular person's account.

Despite a large number of available methods, the implementation of self-organizing systems, models, and cases does not have universal solutions for such common problems as distributed problem solving, coordination and approval, ethics and communications, and reliability and stability in critical states.

Human behavior brings uncertainty and unpredictability to the operation of digital systems, because people often do not act according to some preset rules or models. Hence, predictive modeling of human behavior cannot be reliable enough, although a fully developed digital infrastructure could limit any rule violations in the system to a considerable extent. Along with the advancement of research on human behavior, the main contributions toward a solution to those problems should come from further development of the models that replace humans in the processes, such as intelligent agents, digital twins, bots, etc. Such models can help reduce the risk of accidental errors as well as the risk of deliberate but unforeseen actions and decisions.

To provide communications, the system makes extensive use of multi-agent systems. Not only do they support human-to-machine and machine-to-machine interactions during cooperative activities, but they also ensure compliance with the system's rules, taking into account the interests of the system's elements they represent.

It is interesting to assess the level of self-organization in networked dynamical sociotechnical systems. Depending on the goals and objectives of the system, as well as its size, there may be different requirements for the level of its self-organization. Consequently, different implementations of self-organization could be chosen. One of the most difficult tasks is finding a balance between the development of rules and the maintenance of individual autonomy of the system's elements.

As shown in Ref. [130], self-organized systems do not always exhibit critical properties, hence, SOC or SOC-like and non-SOC processes are distinguished. For some self-organized systems, ensuring the system's stability of operation is one of the goals. The methods of prevention and mitigation of critical events are also of a great interest, as most digital industrial systems fall into this category.

Summarizing the review of models used in mathematical modeling of self-organizing digital distributed systems, it should be noted that the modeling of the micro level of systems based on the use of discrete models prevails.

This approach allows one to take into account more details of a real system, although it complicates the analysis of the model because of a very high dimensionality of the model's global state space [172]. In some cases, discrete models are created ad hoc [173–177]; in other cases, discrete models of digital distributed systems are based on analogies with appropriate biological models (the genetic algorithm or the behavioral models of social insects) [179, 180]. As for the macro-level continuous models of digital distributed systems, they significantly reduce the micro-level state space dimensionality by using equivalence classes. Normally, such models also use analogies, either from biology (population dynamics models) [182, 183] or fluid dynamics [184, 185].

Data Availability

All the data generated or analyzed during this study are included within this article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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