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State-of-the-Art Development of Complex Systems and Their Simulation Methods

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Abstract: The research on complex systems is different from that on general systems because the former must consider self-organization, emergence, uncertainty, predetermination, and evolution. As an important method to transform the world, a simulation is one of the most important skills to discover complex systems. In this study, we provide a survey on complex systems and their simulation methods. Initially, the development history of complex system research is summarized from two main lines. Then, the eight common characteristics of the most complex systems are presented. Furthermore, the simulation methods of complex systems are introduced in detail from four aspects, namely, meta-synthesis methods, complex networks, intelligent technologies, and other methods. From the overall point of view, intelligent technologies are the driving force, and complex networks are the advanced structure. Meta-synthesis methods are the integration strategy, and other methods are the supplements. In addition, we show three complex system simulation examples: digital reactor simulation, simulation of a logistics system in the industrial site, and crowd evacuation simulation. The examples show that a simulation is a useful means and an important method in complex system research. Finally, the future development prospects for complex systems and their simulation methods are suggested.

Key words: systems science; complex systems; complexity; complex system simulation

1 Introduction

In 1999, a special issue on complex systems (e.g., including research papers on complexity and the nervous system, life after chaos, complexity, and economics) was published in *Science*[1]. This article made people suddenly realize that complex systems are rising as a new hot spot. The overall system can be divided into the simple system, simple giant system, and complex giant system. Among them, many types of subsystems with hierarchical structures exist, whose relationship is very complex. Such a system is called an Open Complex Giant System (OCGS) or simply a complex system[2–4].

Typical complex systems incorporate complex networks, macroscopic and microscopic physical systems, complex engineering systems, complex control systems, biological systems, complex chemical and chemical systems, astronomical systems, economic systems, and military countermeasure systems[5–7]. Another example is the recent outbreak of the coronavirus disease 2019 (COVID-19) pandemic[8, 9], which in essence also belongs to the category of complex systems. The research on complex systems has epoch-making significance.

At present, the combination of modeling and simulation technology and high-performance computing technology is becoming the third important method to understand and transform the objective world after theoretical research and experimental research. In view of the particularity of the complex system itself, modelings and simulations are effective

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research methods, which are also necessary for the development of complex systems. From another point of view, the complex system is also necessary for the current stage of development after the constant updating of simulation research. Therefore, the integration of complex systems and simulation[10] is a perfect match.

This study reviews the research progress on complex system simulations. Section 2 discusses the history of complex systems and summarizes their common characteristics from the perspective of a large number of complex systems. Section 3 elaborates on complex system simulation methods. Section 4 describes three examples of complex system simulations. Section 5 shows the future development of complex systems and their simulation methods. Section 6 summarizes the whole paper.

2 Complex System

2.1 Development history of complex systems

Here, we present a brief review of the historical evolution of complex system research, which has two main lines: complexity science and systems science.

From the perspective of complexity science, Austrian biologist L. V. Bertalanffy first established the concept of complexity[11], which was regarded as the starting point of complexity science. Later, the dissipative structure theory of Prigogine and Nicolis[12] and the synergetics of Hagen[13] both made significant breakthroughs in the characteristics of self-organization for complex systems. From the current perspective, their discoveries are still at the level of simple giant systems.

The American scholar Simon presented the idea of artificial science in 1969[14], which connected many disciplines, including economics, cognitive psychology, learning science, design science, management science, and complexity research. His monograph, *Artificial Science* (including three editions), is of great significance to complexity science[14–16].

In 1985, the *Journal of Complexity* was founded. This specialized journal has provided an important platform for the study of complexity, which plays a very direct role in promoting complexity[17].

In 1987, the Santa Fe Institute (SFI) in the United States proposed the idea of the edge of chaos[18], established a new research field called complexity science, and used computers as a means of performing complex scientific research. The researches[18] utilized computers to simulate interrelated complex networks, which also played a very important role in promoting complex system simulations. Nowadays, SFI still occupies an important position in the research of complex systems around the world. Later, Holland proposed the concept of Complex Adaptive Systems (CASs)[19]. CASs emphasize the use of computer simulations as the main means of research. CASs are the key research objects of SFI and also a hot topics at present.

In 1999, a special issue on complex systems appeared in *Science*, in which the research topics included complexity in the nervous system, complexity in biological signaling systems, simple lessons from complexity, complexity in chemistry, complexity and climate, and complexity and the economy[20]. Hence, to some extent, the research on complex systems is highly valued by the international academic circle.

In 2013, the *Journal of Complex Networks* was founded[21]. Complex networks are important parts of complex systems. This journal also has a certain impetus to the study of complex systems.

In 2021, a high-level international journal called *Complex System Modeling and Simulation* was founded[22]. This journal is of great significance to the research on complex systems and their simulation theories and methods.

The other main line is the research from the perspective of systems science, which mainly focuses on OCGSs led by Chinese scientist Xuesen Qian. In 1954, Qian published the monograph *Engineering Cybernetics*[23], which made a comprehensive discussion on engineering technology, automatic control, and automatic regulation theory of various systems.

In the research process of systems science, Xuesen Qian started to analyze and refine the concept of OCGSs. Since 1979, three systems have been developed: giant systems, complex giant systems, and OCGS. By the fall of 1989, the concept of OCGSs had been developed, in which OCGSs were regarded as an important topic of basic science research at the macro level. In Ref. [24], Qian et al. made a comprehensive and systematic discussion of this concept and its methodology.

Along with the concept of OCGSs, Qian and Tsien[25] and Dai[26] also presented the comprehensive integration of qualitative and quantitative methods. Later, Dai and Li[27] proposed the hall for seminar systems of man-machine combination and comprehensive integration from qualitative to quantitative, which is referred to as the hall for seminar systems in short. These works were also collectively referred to as the theory of qualitative-to-quantitative meta-synthesis.

Afterward, in 2004, Wang et al.[28] proposed the combination of an artificial system, computational experiment, and parallel system with the comprehensive integration method from qualitative to quantitative and parallel distributed high-performance computing technology. Thus, diversification and integration of complex system research methods were further advanced. In this year, the journal *Complex Systems and Complexity Science*[27] was founded, which also provided a platform for communication on complex system issues.

The theory of qualitative-to-quantitative meta-synthesis provided a breakthrough and effective methodology for understanding and solving the problem of OCGSs. Moreover, in 2009, Cao et al.[29] proposed the concepts of M-Interaction, M-Space, and M-Computing, which are the three key components for studying OCGSs and constructing problem-solving systems.

Based on deep learning and big data, the third upsurge of artificial intelligence was set off by AlphaGo and other typical application scenarios[30]. The traditional artificial intelligence based on statistical linearization and dynamic modeling has encountered the development bottleneck of interpretability, generalization, and reproducibility when dealing with complex systems. In 2021, Zheng et al.[31] established a new generation of artificial intelligence theory based on complexity and multiscale analysis, which is called the refined intelligence theory. This is a significant achievement as a new meta-synthesis for complex system research from the viewpoint of intelligent science.

Figure 1 shows the two main lines of the

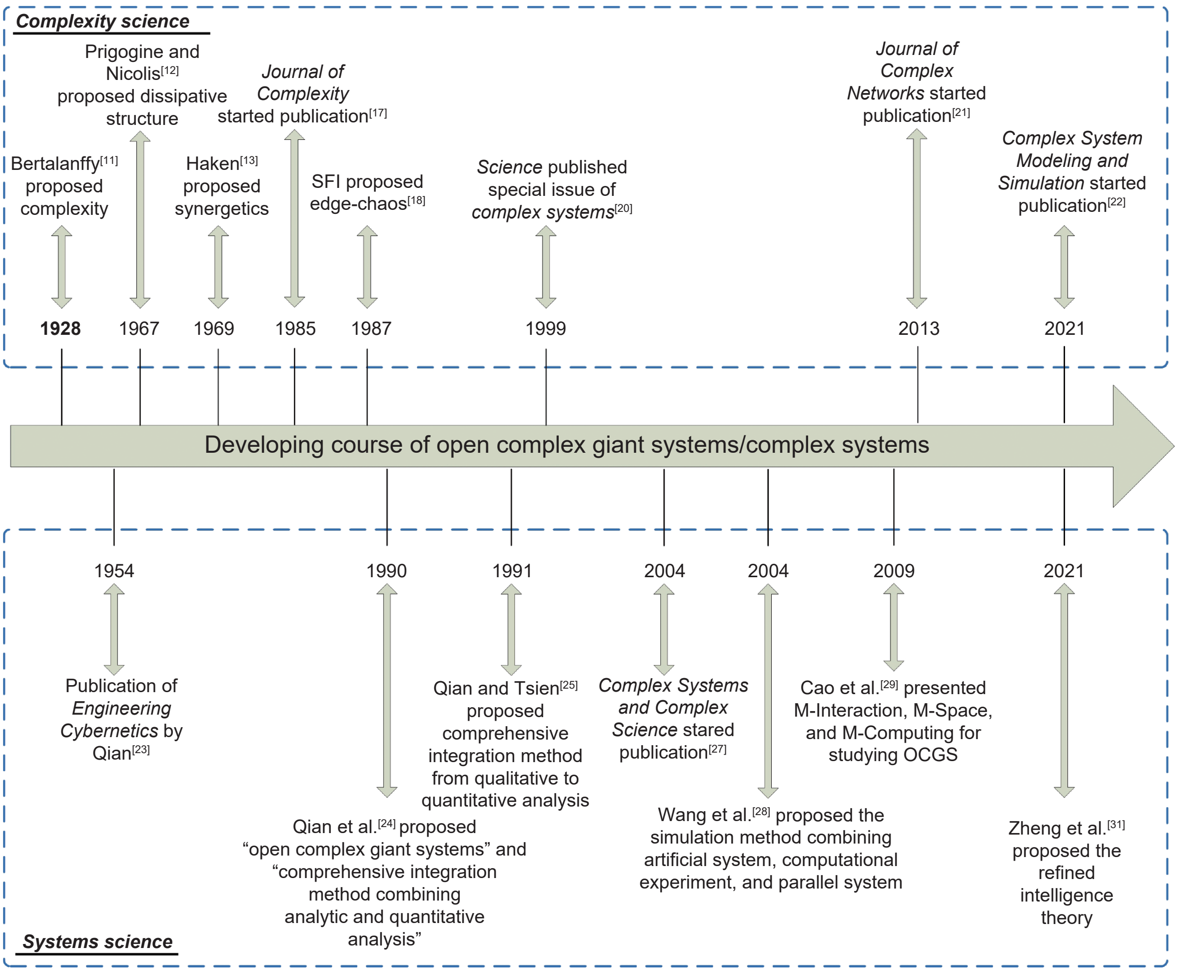


Fig. 1 Development course of complex systems.

development course of complex systems.

2.2 Characteristics of complex systems

The main characteristics of complex systems are as follows[32, 33]:

(1) Nonlinearity

A complex system is composed of many elements or subsystems, and the overall behavior and characteristics of the system are not equal to the linear superposition of the behavior or characteristics of its internal elements or subsystems. Such a system is called a nonlinear system. Because of the nonlinearity of the system, when a new system is formed from elements or subsystems, it will exhibit new characteristics different from those of elements or subsystems.

(2) Self-organization

A system is made up of overlapping or distributed space-time components. These components have self-adaptation, self-learning, self-aggregation, and self-organization abilities. Through continuous learning, the components can adjust their own structure and behavior to adapt to external and internal changes. The autonomy of the components and the complexity of their interactions make the whole system appear complex. Nonlinearity is also a driving force for the evolution of complex systems.

(3) Uncertainty

Uncertainty is related to chaos, which can simply be considered deterministic randomness. The deterministic property means that it is produced by an internal cause rather than an external noise or disturbance; that is, the process is strictly deterministic. Randomness refers to irregular and unpredictable behaviors. Chaos cleverly integrates the disorder of expressions with the internal determinism mechanism. Following the order of expression, there is strange chaos, and in the depth of chaos, there is a more strange order.

(4) Emergence

Emergence is a local interaction between neutron systems or basic units that, over time, develops unique and new properties and patterns on the whole. This process is called emergence. The interactions between subsystems can lead to macroscopic wholeness properties that significantly differ from the behaviors of individual subsystems. Emergence is also a qualitative change. After the interaction between the subjects begins, the system can acquire self-organization, self-coordination, and self-strengthening abilities and develop them accordingly. Finally, there is a qualitative change, which is called emergence.

(5) Predetermination

The development trend of complex systems depends on their predetermination, which is the unity of the expectation of the future state and the limitation of the actual state. Any living matter has the ability to anticipate or predict and thus influence the direction of the system’s movements.

(6) Evolution

A complex system presents the processes of expectation, adaptation, and self-organization for the external environment and state, which leads to the continuous evolution of the system from function to structure[34]. This kind of evolutionary movement does not exist in physical systems. A physical system typically consists of several existing elements with no change in function or structure. The complex system is generally a simple combination of elements through continuous evolution to develop into a more complex system in terms of function and structure. An essential characteristic of a complex system is the continuous evolution from low level to high level and from simple to complex.

(7) Openness

Openness manifests itself as the most complex and common type of uncertain, dynamic, and continuous environment. Complexity is reflected not only in the system itself but also in the environment. The disorder of a system is described in terms of entropy. The internal entropy of an isolated system will increase with time until it reaches its maximum value, and the system tends to be out of order. Different from an isolated system, an open system constantly exchanges energy, material, and information with the outside environment. This exchange allows importing negative entropy from the external environment, so the total entropy of the system is reduced or controlled at a slow growth rate. As a result, the order of the system is increased, which is the value of openness.

(8) Cascade failures

Due to the strong coupling among components in a complex system, the failure of one or more components may lead to cascading failures[35]. This situation can have disastrous consequences for the operation of the system. Local attacks can cause cascading failures or sudden collapses of space networks. This condition is highly similar to the butterfly effect.

3 Complex System Simulation Methods

3.1 Meta-synthesis methods

The OCGS problems are very challenging because of their inherent system complexity. An empirical conclusion is that, in the 1990s, some famous Chinese scientists put forward a new scientific field, i.e., the qualitative-to-quantitative meta-synthesis methodology. It comprehensively reveals the complexity of a system, the cognitive process of humans, the role difference between humans and machines, and the possible research direction. The qualitative-to-quantitative meta-synthesis incorporates the comprehensive integration method of the qualitative and quantitative combination, the comprehensive integration method from the qualitative to the quantitative, and the hall for seminar systems. Moreover, the simulation method combining an artificial system, computational experiment, and parallel system proposed by Wang et al.[28] can be incorporated into such a meta-synthesis methodology. In fact, research and practice have shown that qualitative-to-quantitative meta-synthesis is an appropriate method to build a problem-solving system when dealing with OCGSs.

Cao et al.[29] illustrated their understanding of meta-synthesis from the perspective of human, machine, and human-machine social cognitive interactions. They put forward the concepts of M-Interaction, M-Space, and M-Computing. M-Interaction constitutes the main problem-solving mechanism of the qualitative-to-quantitative meta-synthesis. M-Space is the OCGS problem-solving system embedded with M-Interactions. M-Computing consists of the engineering methods of analyzing, designing, and implementing the M-Space and M-Interaction compositions. In support of this theory, they demonstrated the theoretical framework of M-Interaction-based OCGS problem solving through M-Space, problem-solving process, emergence of social intelligence, and thought traps. Starting from the problem solving of OCGSs, they attempted to connect and develop the knowledge of multiple disciplines while emphasizing the role and principles of the problem-solving process based on the M-Interaction and M-Space system. These results contribute to the formation of the framework, working mechanism, cognitive-interaction model, cognitive evolution, and intelligent emergence of problem-solving M-Spaces for OCGSs.

The main strategies in this field include the following:

- The comprehensive integration of qualitative and quantitative methods;
- The comprehensive integration method from qualitative to quantitative;
- The hall for seminar systems;
- The simulation method combining an artificial system, computational experiment, and parallel system;
- M-Space, M-Interaction, and M-Computing.

3.2 Complex networks

The study on complex network theory can be traced back to the problem of Seven Bridges proposed by the Swiss mathematician Leonhard Euler in the 18th century[36]. This problem abstracted the land as a point, and the bridge connecting the land as an edge, and the points and edges connecting the points constitute a network[36]. With the rapid development of complex systems, the analysis of the complex network method has been widely applied in social, economic, military, and other fields, such as online social networks, international trade, and modern information warfare systems.

Generally, a network in part or in whole properties (including self-organization, self-similarity, attractor, small world, and scale-free properties) can be called a complex network. When studying a network, people tend to only pay attention to whether there is an edge between nodes and ignore factors, such as node location and edge properties. A complex network can be regarded as a high abstraction of the complex system. The nodes in the network are abstracted as individuals in the complex system, and the edges in the network are abstracted as the relationships among individuals in the complex system. In this way, the network formed by a large number of nodes and mutually connected edges among nodes can be called a complex network.

The research points of complex networks mainly include the following aspects[36–39]:

- **Research on community structure**

Based on connectivity, a community can be regarded as a faction, that is, a fully connected subgraph composed of more than two nodes, with connecting edges between any two nodes. How to detect and divide the community structure hidden in a complex network is an important content in complex network research.

● **Research on survivability**

Network survivability can be understood as the resilience or adaptability of a network when it is attacked or fails or the ability to continue to provide services in the case of partial node or edge failure. The specific research points include the index measure and strategy optimization of survivability.

● **Research on node influence**

The small-world effect and scale-free characteristics make the distribution of nodes in complex networks appear uneven, and a few nodes have several connections and play an important role. Therefore, the accurate identification of the important nodes in the complex network is of great significance for optimizing the structure and function of the complex network. The research on node influence includes the ranking of node importance and maximization of node influence.

● **Research on information communication**

Research on the dynamic mechanism of information dissemination on social networks is the basis of effective risk management and control. The establishment of an appropriate information transmission model can accurately reflect the change in information transmission among individuals in the network over time. The key is the exploration of the typical information transmission model.

● **Research on synchronous control**

Synchronous control in a complex network involves controlling the network by applying external forces to make the internal dynamic systems of multiple nodes reach the same state and maintain stability. How to control the synchronization of complex networks so as to maintain the beneficial synchronization and avoid harmful synchronization has become a hot issue. Among them, the containment control strategy is also an important research point.

● **Research on random walks**

Random walking is one of the dynamic behaviors in complex network research, and it is closely related to other behaviors, such as information transmission and synchronization. Random walking on a complex network refers to the following process: First, random walking particles take the complex network structure as the carrier. Second, starting from the initial node, they select the neighbor node of the current node with a certain probability for transmission at each time step. Finally, they arrive at the destination node. The key is the model of random walking.

To accurately describe the network topology of a real system, there are roughly three stages: regular network, random network (the Erdös-Rényi (ER) model), and complex network (small-world network and scale-free network). The complex network has become a new research hotspot in international academic circles. Typical complex network models include the following types:

● **Random graphs and general random graphs**

The systematic study on random graphs began in 1959. The original purpose was to use probability theory to examine how the properties of graphs change with the increase in the number of random connections. A random graph refers to the disordered characteristics of connections between different points, of which the ER random graph is a typical representative. To better express a real network, especially its simple property of having a non-Poisson distribution, the ER model can be extended in different ways and consequently developed into a general random graph. The configuration model introduced by Bender and Canfield[40] can build graphs according to degree sequences. The simplicity of the configuration model makes it a good analytical method.

● **Small-world network model**

Generally, if the average path length of a network is proportional to the logarithm of the number of nodes, then the network is said to have a small-world effect. Most real complex networks have the small-world effect; that is, they have a small average path length and large agglomeration coefficient. Based on this point, Watts and Strogatz proposed the small-world network model (the Watts-Strogatz (WS) model)[41]. In a circular regular network, each node is accessed in a clockwise direction, and an edge connected to the current node is selected. Each edge is deleted and reconnected with a probability of p, and the other end of the edge is randomly connected to other nodes. In this process, long-range edges may appear to reduce the average path length of the network, preserving the original edges with the probability $1-p$. Repeated connections and self-loops are not allowed in the whole process. The probability value can be changed to adjust the randomness of the network and keep the balance of the number of edges in the network. The small-world network constructed by this method has a small average path length and large agglomeration coefficient. Considering that the construction method of the WS model may destroy the connectivity of the network, Newman and Watts improved it and proposed the Newman-Watts (NW) model[42]. The improvement of the NW model is that the random reconnection is replaced by random edge addition. In other words, connecting edges are added between randomly selected node pairs with probability without changing the original connecting edges, and repeated connections and self-loops are not allowed. When the network size is large enough and the probability is small enough, the WS and NW models are essentially the same.

- **Scale-free network model**

In random and small-world networks, the degree distribution of nodes is approximately a Poisson distribution. However, researchers found that the degree distribution of most real complex networks follows the power law distribution. In details, Barabási et al.[43] proposed the scale-free network model (Barabas-Albert (BA) model). This model can be described from two aspects: network growth and priority connection. Network growth means that new nodes in the network are constantly joining and connecting the existing nodes. Priority connection means that the newly added node will give priority to the node with a higher connection value. The results show that the BA network not only has a small-world effect and large cluster coefficient, but also its degree distribution satisfies the power law distribution. Another type of model is the evolution network inspired by protein interactions.

- **Space networks**

A special type of network is one that is embedded in a physical space, in which points occupy a definite location in two or three dimensions. Their edges are actual physical connections. Typical examples are neural networks, information and communication networks, power networks, transportation systems, and ant colonies.

- **Local-area world network model**

The preferential attachment mechanism in the BA model exists in the global network. However, based on the research on real complex networks, Li and Chen[44] found that the preferential attachment mechanism exists only in local networks. Based on the BA model, a simple local-area world network model (Li-Chen (LC) model) was proposed. In the LC model, several nodes are randomly selected as the local world of the new node. The new node would give priority to connect to the node with a higher medium value in the corresponding local world rather than the node with a higher medium value in the global network. In the BA model, new nodes have global information. In the LC model, new nodes only have local information. In a real complex network, there are always a few nodes with global information, and most nodes only have local information. Based on this information, Qin and Dai[45] improved the LC model and established a new local-area world network model. In this model, the ratio of the number of global nodes to the number of summary points is introduced as the probability that new nodes belong to global nodes. It takes the LC and BA models as its special cases.

- **Weighted network**

The above network models all networks as nonweighted networks, ignoring the degree of interaction between nodes or the physical quantities of nodes and edges. However, the real network is usually the weighted network with weighted nodes or edges. Compared with a nonweighted network, a weighted network can better reflect the real situation. Yook et al.[46] proposed a simple weighted network model based on the BA model, which describes the strength of interaction between nodes and the heterogeneity between connecting edges by giving edge weights. Barrat et al.[47] proposed the Barrat-Barthélemy-Vespignani (BBV) model. In this model, the influence of the topological structure and weight on the dynamic evolution of the network is considered comprehensively. With the increase in the network size, the degree distribution, edge weight distribution, and node weight distribution all have scale-free characteristics. Another mechanism similar to the BBV model is the Dorogovtsev-Mendes (DM) model.

3.3 Intelligent technologies

Intelligent technologies play an important role in complex system simulations, and several main methods are described here.

(1) Refined intelligence

Focusing on the nonlinear random correlation between system elements, refined intelligence[31] integrates statistics, analysis, algebra, geometry, dynamic system, and other theories. Focusing on the basic intelligence architecture of the data-model algorithm (i.e., knowledge system learning), it focuses on the interpretability of artificial intelligence. By studying the multilevel and multiscale correlation and coupling mechanism of complex systems and the spatiotemporal dynamic structure, it aims to develop an intelligent theoretical system that embeds underlying logic and mathematical physics and integrates nonlinear analysis and complexity science. The accurate cognition and intelligent learning methods of big data are established from three levels, namely, complex data scientific perception, accurate construction of complex systems, and intelligent analysis of complex behaviors. These form the core of refined intelligence.

To be specific, refined intelligence examines basic scientific problems, including the paradigm of scientific data descriptions based on spatiotemporal characteristics and mathematical laws, reconstruction methods of mathematical systems based on coupling and decoupling methods of complex data systems, complexity classification of the intrinsic and dynamic features of complex systems, global structure analysis based on local morphological features, and system mutation based on the threshold analysis. It establishes the accurate cognitive theory and fast mining method of big data from the perspective of systems science.

From the perspective of complexity science, refined intelligence constructs a new theoretical framework that can explain artificial intelligence based on the logic relations of complex systems. It aims to reveal the nonlinear relationship of multivariable main factors in complex systems from the perspectives of the complexity of scientific description, data system structure, and system behavior evolution of big data. Through multilevel and multiscale coupling association modeling, the intrinsic law is explained. This law focuses on the influence of multiscale mechanisms and effects on the system, dynamically identifies the complex characteristic behavior patterns of the system, and forms a method system that can explain artificial intelligence. Its research directions mainly include complex data science perception using unit data to build overall data[48–50], accurate construction of complex systems using data systems to build intelligent learning models[51–53], and intelligent analysis of complex behaviors using learning models to analyze the evolution of system features[54–56]. The refined intelligence theory is applied to swarm intelligence, and the swarm entropy method is proposed, in which the complexity of group excitation and convergence behavior is measured and effectively guided and regulated.

(2) Deep learning

Deep learning models can be considered neural networks with deep structures. The history of neural networks can be traced back to the 1940s. Its original purpose was to mimic the human brain system for solving general learning problems in a principled manner. With the principle of the backpropagation algorithm proposed by Rumelhart et al.[57], neural network algorithms became popular. However, because of the lack of large scale, excessive training data fitting, limited computing power, and the lack of performance compared with other machine learning tools, such as faults, by 2000, the study on neural network algorithms tended to be cooled, in which the number of studies decreased. In 2006, Hinton and Salakhutdinov[58] and Hinton et al.[59] formally proposed the concept of deep learning. Later, breakthroughs in speech and image recognition technology have ignited enthusiasm for deep learning research. It has become an extremely hot branch of machine learning[60, 61]. Deep learning has been an important method to simulate and study complex systems. For example, Refs. [62–65] showed the use of deep learning to research robot navigation systems, complex multiagent systems, complex fault diagnosis systems, and complex traffic systems.

(3) Artificial life

Artificial life[66, 67] is a simulation, extension, or extension of natural life. It is a man-made system with internal properties or external behaviors similar to those of natural life. The research field covers the laws, testing, simulations, and bionic applications of various abstract life forms (e.g., cellular automata) and simulation life forms (e.g., electronic cell, artificial plant, artificial animal, artificial brain, and robot). Artificial life was first proposed to use computer simulations to explore the law of life movements. The subject of artificial life is concerned with complex autonomous systems with emergent characteristics. Because of the characteristics defined by separable and unknowable hypotheses, it is impossible to use the top-down analysis method to predict results. Therefore, we must observe the law of its change and development through simulation experiments[68, 69]. Because this kind of experiment is concerned with the evolutionary characteristics[70] of experimental subjects, it is also called an evolutionary simulation. However, the simulation of this kind of complex autonomous system usually requires a large amount of computation. One of the solutions to the large amount of computing is distributed computing. Evolutionary simulations are highly effective when used with various subjects. Spatiotemporal coupling presents a unique challenge to the design of its distribution strategy.

Other methods are presented as follows[71–75]:

- Neural network;
- Genetic algorithm;
- Gene networks;
- Cellular automata;
- Constrained production process model;
- Particle swarm optimization algorithm;
- Agent-based modeling and simulation; and
- Group method of data handling.

3.4 Other methods

Many other methods have also been proposed:

(1) Visualization

A simulation is inseparable from visualization[76, 77], and the visualization of simulation results has become a convention of a simulation. However, because the modeling of complex systems is also extremely difficult, the introduction of visualization in the early stage[78, 79] not only makes the modeling of complex systems more clear and visible but also contributes to the early participation of human thinking. It can promote the correctness of modeling and the understanding of the nature of complex systems to a certain extent.

Our research group at the Hefei University of Technology has performed considerable work on visualization[80–82]. For more than 20 years, relying on visual environments, our research group has systematically and deeply studied template theory, intelligent design, motion simulation, and visualization methods, which are guided by the modeling methodology, based on collaborative computing, and rely on visual environments[83–85]. The research work on visualization combined with the simulation of verification, validation, and accreditation has conducted a comprehensive study on the simulation of complex systems, which can be further detailed in the following examples.

(2) Petri net

A Petri net[86, 87] is a mathematical representation of discrete parallel systems. Petri nets were invented by Carl A. Petri in the 1960s to describe asynchronous, concurrent models of computer systems. A Petri net has not only strict mathematical expression but also intuitive graphic expression, rich system description means, and system behavior analysis technology.

This method is a graphical research tool composed of databases, transitions, and directed arcs connecting the former two[88, 89]. It is a theory used to study the organizational structure and dynamic characteristics of a system and is especially suitable for modeling and analyzing asynchronous concurrent systems. It can fully describe the system characteristics of concurrency, asynchrony, nondeterminism, and parallelism. In complex systems, object-oriented technology and Petri net technology are commonly combined, which is called an object-oriented Petri net (OOPN). An OOPN can simplify the technical model of Petri nets but also make the expression intuitive. At present, Petri nets can be applied to complex systems, such as diagnosability analysis, complex control systems, and complex manufacturing systems[90–92].

(3) Fuzzy system based method

Based on fuzzy mathematics, the uncertainty of observed data is dealt with by the fuzzy mathematics method on the basis of establishing a model framework. Fuzzy systems[93, 94], based on the macroscopic point of view, grasp the characteristics of the fuzziness of the human brain and have their own advantages in describing high-level knowledge.

Fuzzy systems are composed of the fuzzy reasoning method[95–97] and fuzzier, defuzzier, and fuzzy rule bases. They can deal with fuzzy information processing problems, which are difficult to be solved using conventional mathematical methods that imitate human’s comprehensive inference[98–102]. They enable computer applications to be extended to the fields of humanities, social sciences, and complex systems.

Some other methods are listed as follows[103–107]:

- Parameter optimization method;
- Macro simulation method;
- Task/resource map;
- Knowledge-driven method;
- Formal method of system theory;
- Qualitative causal method;
- System dynamics;
- Inductive reasoning;
- Metamodel;
- Fractal; and
- Systems engineering analysis.

3.5 Summary of methods

In summary, complex system simulation methods can be divided into four categories. The overall research layout is shown in Fig. 2.

For the simulation methods of complex systems, eight characteristics that may be reflected are considered, as shown in Table 1 (in which Y represents the simulation method that can embody such characteristics).

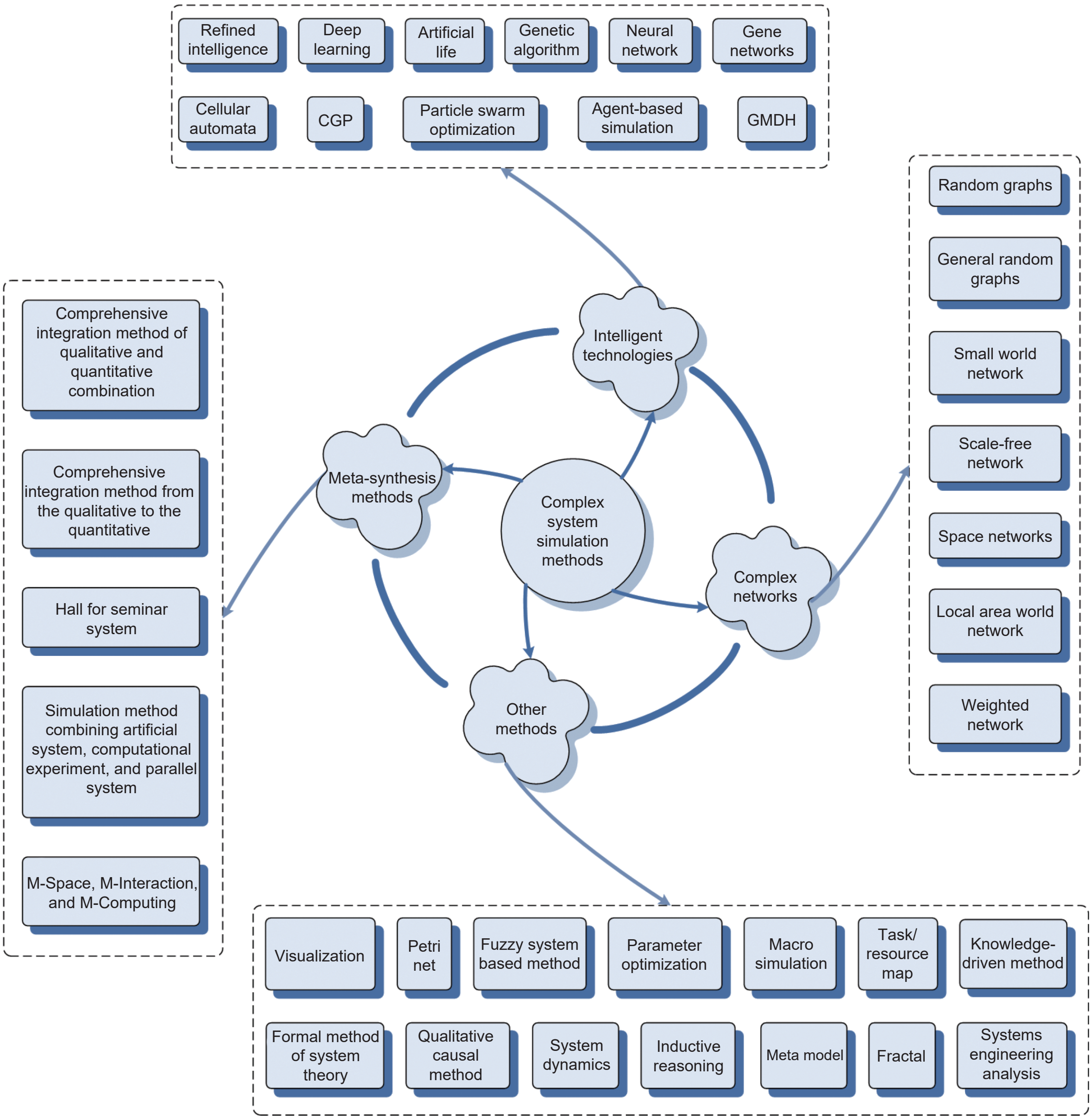


Fig. 2 Research layout of complex system simulation methods.

4 Examples of Complex System Simulation

4.1 Digital reactor simulation

After more than 60 years of rigorous development, the development strategies of magnetic confinement fusions in the world have gone through several stages, such as plasma experimental equipment, experimental reactors, demonstration reactors, and large-scale commercial reactors. The design of a fusion reactor has always been an important aspect of fusion research because it typically takes a long time (approximately 10 years) and costs a lot (approximately $10 billion) to build a large complex device, such as a fusion reactor. Its design is different from that of general installations. It undergoes a comprehensive process integrating the physical design, conceptual design, technical design, environmental assessment, and economic assessment. The design of a reactor has become a key issue in the field of nuclear energy. Because the engineering plan of advanced nuclear power systems has not been finalized, the research on new reactors is currently in the conceptual design stage of comparing several plans. In the later stage, people should undergo from conceptual design to geometric design and then to simulation and scheme evaluation, which is a time-consuming and labor-consuming cycle.

To sum up, fusion reactors are a complex engineering system with the following characteristics:

Table 1 Eight characteristics reflected by complex system simulation methods.

Major category of methods	Specific method	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Meta-synthesis method	Comprehensive integration method of qualitative and quantitative combination	Y	Y	Y	Y	Y	Y	Y	Y
	Comprehensive integration method from the qualitative to the quantitative	Y	Y	Y	Y	Y	Y	Y	Y
	Hall for seminar system	Y	Y	Y	Y	Y	Y	Y	Y
	Simulation method combining artificial system, computational experiment, and parallel system	Y	Y	Y	Y	Y	Y	Y	Y
	M-Space, M-Interaction, and M-Computing	Y	Y	Y	Y	Y	Y	Y	Y
Complex network	Random graphs	Y	−	Y	Y	Y	Y	Y	Y
	General random graphs	Y	−	Y	Y	Y	Y	Y	Y
	Small world network	Y	Y	Y	Y	Y	Y	Y	Y
	Scale-free network	Y	Y	Y	Y	Y	Y	Y	Y
	Space networks	Y	Y	Y	Y	Y	Y	Y	Y
	Local area world network	Y	Y	Y	Y	Y	Y	Y	Y
	Weighted network	Y	Y	Y	Y	Y	Y	Y	Y
Intelligent technology	Refined intelligence	Y	Y	Y	Y	Y	Y	Y	Y
	Deep learning	Y	Y	Y	Y	Y	Y	Y	Y
	Artificial life	Y	Y	Y	Y	Y	Y	Y	Y
	Genetic algorithm	Y	Y	Y	Y	Y	Y	Y	−
	Neural network	Y	Y	Y	Y	Y	Y	Y	Y
	Cellular automata	Y	Y	Y	Y	Y	Y	Y	Y
	CGP	Y	Y	Y	Y	Y	Y	Y	Y
	Particle swarm optimization	Y	Y	Y	Y	Y	Y	Y	Y
	Agent-based simulation	Y	Y	Y	Y	Y	Y	Y	−
	GMDH	Y	Y	Y	Y	Y	Y	Y	Y
Other methods	Visualization	Y	Y	Y	Y	Y	Y	Y	Y
	Petri net	Y	−	−	Y	Y	Y	Y	Y
	Fuzzy system based method	Y	Y	Y	Y	Y	Y	Y	Y
	Parameter optimizationv	Y	Y	Y	Y	Y	Y	Y	−
	Macro simulation	Y	Y	Y	Y	Y	Y	Y	Y
	Task/resource map	Y	−	−	Y	Y	Y	Y	Y
	Knowledge-drived method	Y	−	−	Y	Y	Y	Y	Y
	Formal method of system theory	Y	−	−	Y	Y	Y	Y	Y
	Qualitative causal method	Y	−	−	Y	Y	Y	Y	Y
	System dynamics	Y	−	−	Y	Y	Y	Y	Y
	Inductive reasoning	Y	−	Y	−	Y	Y	Y	Y
	Metamodel	Y	−	Y	Y	Y	Y	Y	Y
	Fractal	Y	−	−	Y	−	Y	Y	Y
	Systems engineering analysis	Y	−	Y	Y	Y	Y	Y	Y

(1) Intersecting in multiple fields;

(2) Structural complexity;

(3) Numerous and complex objective optimization parameters; and

(4) Massive data and a huge amount of computation.

We use the simulation method to examine such reactors and put forward the concept of digital reactors. The so-called digital reactors refer to a comprehensive application platform for storing, processing, and expressing various reactor data based on an existing physical model, which relies on computer hardware and uses various software technologies. A digital reactor provides an efficient and convenient research platform for domain experts and can show the design intention of domain experts in real time. It will greatly improve the working efficiency of field experts and liberate them from heavy repetitive works. Accordingly, field experts can focus on the most important link in reactor research and can further discover and explore laws. Such development allows costly experiments to be repeated and makes impossible things possible.

The digital reactor system has a large scale and involves several fields, hardware, and software. The main model of the digital reactor is shown in Fig. 3. The core technologies of the digital reactor are as follows:

(1) Distributed simulation and computing technology

It uses the local-area network to connect and is composed of a highly complex topology structure.

(2) Cluster computing technology

Because of the large amount of simulation computations and data, the data to be processed are calculated using six node clusters.

(3) Multidimensional integrated visualization

First, the multiviewport visualization technology is used for multivariable data, and the visualization method of displaying multiple windows can be adopted, as shown in Fig. 4. Each window displays different data of different variables to facilitate the understanding of the relationship between multidimensional data. Second, stereoscopic display technology adopts active and passive stereoscopic display methods to realistically reproduce complex data fields, as shown in Fig. 4. Finally, the simulation data dimensional-increasing visualization technology artificially elevates low-dimensional data to a higher dimension by adding necessary physical information. It uses the high-dimensional visualization method to clearly display data and deepen the understanding of the data.

Fig. 4 Multiviewport visualization technology.

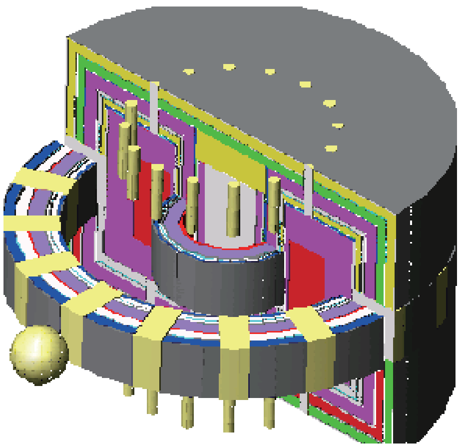


Fig. 3 Main model of the digital reactor.

(4) Virtual reality technology

Using virtual reality technology through three-dimensional (3D) display mode, the observer can roam in a 3D data field in real time. Thus, data field rules can be seen clearly and directly, and the reactor design process and efficiency can be accelerated.

(5) Multiple intelligent modeling techniques

The genetic algorithm and parallel genetic algorithm are applied to reactor core parameter optimization and plasma equilibrium optimization modeling and optimization processes.

4.2 Simulation of the logistics system in industrial sites

Industry 4.0 is embodied in the development of fully automated production lines in modern factories. Materials are processed, transported, or stored under the automated program of various facilities. The entire workshop may be composed of different automated lines, each of which contains multiple types of production, processing facilities and logistics facilities. The industrial field system fully embodies the complexity brought about by multifacility cooperative work. It can be summarized with the following characteristics:

(1) Nonlinearity

There are many types of facilities in industrial sites. Standardized and nonstandardized facilities, domestic and foreign facilities, and new and traditional facilities exist in the same system, but the quality is not unified.

(2) Self-organization

Various facilities on industrial sites need to work together to process, transport, or store products. At the same time, the spatial layout of various facilities will have an important impact on the efficiency of the workshop, so the layout design is very important.

(3) Uncertainty

The facility failure is incidental, and it is impossible to estimate the timing and extent of the impact.

(4) Cascade failures

In the actual production process, the failure of any facility will have an impact on the driving process of front and rear facilities, which may destroy the entire automated process.

The traditional workshop layout design is guided by the experience of designers to estimate the operating efficiency and produce the computer-aided design drawings of facility layouts. However, it has the following shortcomings: It heavily relies on the experience of designers and lacks 3D space expression. Thus, the workshop efficiency calculation is not accurate, and it is impossible to predict the possible failure problems during the actual operation. The 3D simulation software that assists industrial process designers in designing the layout conveniently and effectively is an effective means to improve workshop operation efficiency and study fault treatment.

Our research group has developed a set of warehouse logistics systems. This system contains the digital model of the main facilities of warehouse logistics and integrates a facility driver script. It supports designers to quickly visualize 3D workshop scenes. It can help identify design errors through simulation processes and perform an efficiency analysis and comparison or simulate fault phenomena. Then, it can adjust the layout of the facilities. System screenshots are shown in Figs. 5 and 6 and Table 2. The technologies and characteristics of the system are as follows:

(1) We design a workshop facility process information model that supports animated simulation scenes. All users need to enter the main parameters and facility associations to build the full scene model.

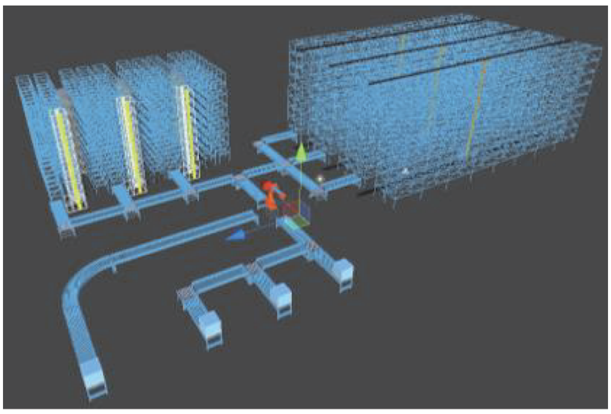
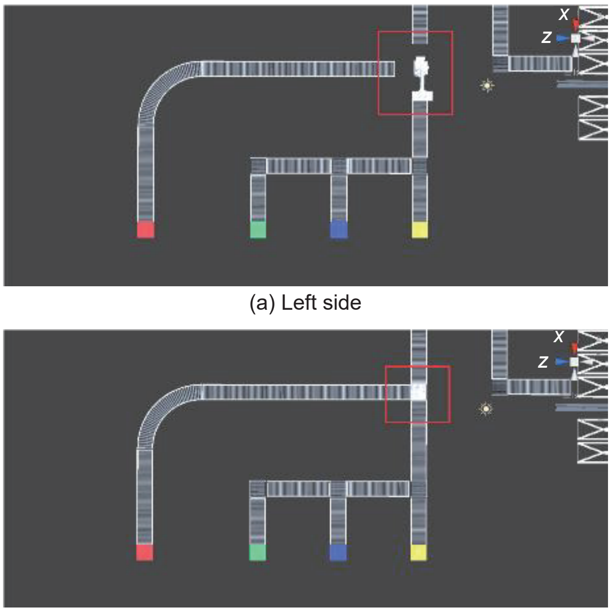


Fig. 5 Warehouse logistics scenario generated from parameterized information.



(a) Left side

(b) Right side

Fig. 6 Simulation comparison results of using two different facilities.

Table 2 Time comparison of using two different facilities for the sorting area.

Cargo	Time for the left side (s)	Time for the right side (s)
No.1: Red cargo	92.99	61.15
No.2: Green cargo	109.23	73.65
No.3: Blue cargo	89.12	73.67
No.4: Yellow cargo	78.34	83.08

(2) It uses the logistics simulation animation generation method based on a state diagram query, which reflects the various facilities of the material transport process.

(3) It can support the quick replacement of facilities and analyze simulation efficiency.

(4) It can display system operating errors or failures in a visual way and prompt users of the possible results of material accumulation.

4.3 Crowd evacuation simulation

With the development of society, the safety of large public places has attracted increasing attention. In these places, many people come and go. In emergency cases, how to evacuate a large number of people safely and quickly is a problem that must be seriously considered in site design. Crowd evacuation can be regarded as a complex system. People’s psychological behavior characteristics in emergency evacuation processes and the impact of these behaviors on emergency evacuation have a great uncertainty and randomness, so the evacuation process is a complex and emergent process. The real evacuation experiment is faced with huge manpower and material resource consumption. The traditional approach used by fire, police, and administrative departments is to conduct costly and real-world exercises. However, it has certain destructiveness and hidden dangers. Using computer simulations instead of physical models and real exercises can be successful to a large extent. Therefore, it is of great practical significance to study the establishment and simulation of evacuation models. Evacuation simulations are an important reference for the architectural design and decision-making of emergency evacuation plans.

Crowd evacuation has the following characteristics:

- **Self-organization**

The crowd can adjust the escape route in real time according to the actual situation.

- **Uncertainty**

People’s psychology, physiology, personality, and other factors bring uncertainty to the impact of survival. Moreover, the environment and disaster development direction have uncertainties.

- **Emergence**

Because of the conformity of the crowd, certain individuals or environmental changes may cause the overall emergent behavior.

- **Predetermination**

Crowds have the ability to anticipate or predict and thus influence the direction of system movements.

Our research group has developed the Campus Evacuation Simulation System (CESS). The purpose is to study the complex evacuation problem through the simulation method. The screenshots of system operation are shown in Figs. 7−9. The techniques and features of CESS are as follows:

(1) Based on the modeling technology of an agent, individual autonomy and self-adaptability are expressed. Thereafter, we comprehensively consider a variety of factors, such as physical condition, degree of rationality, degree of familiarity with the environment, degree of education, and speed of escape.

(2) We use the behavior modeling method to represent the interaction of the crowd, such as collective panic and conformity.

(3) Parallel computing technology is used to improve simulation speed. It can help solve computational problems of large scale, complex environments, and large numbers of people.

(4) Visualization technology is utilized, so the simulation results can be observed in real time and the evacuation effect can be viewed.

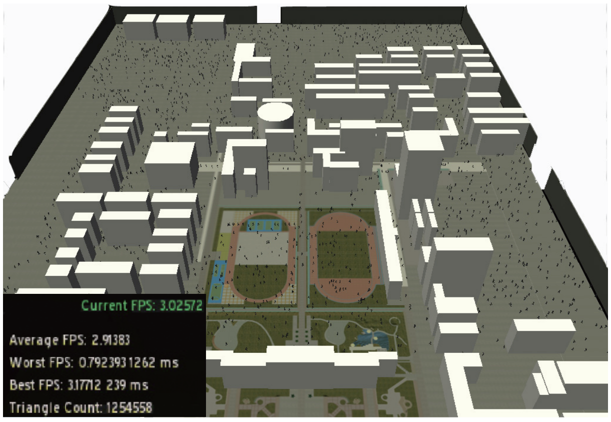


Fig. 7 Overall model and interface of the CESS.

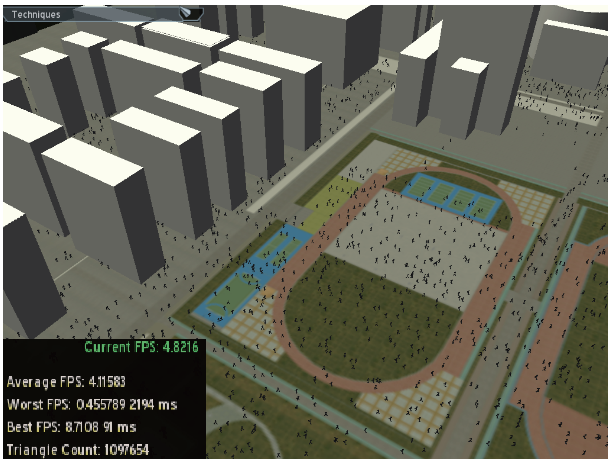


Fig. 8 Close-up of the stadium in the CESS.

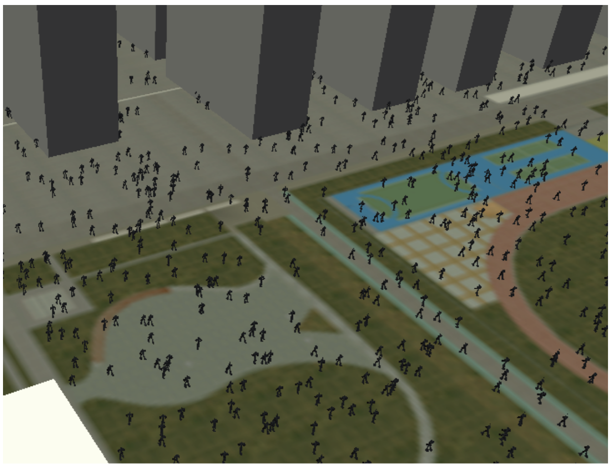


Fig. 9 Close-up of a detail in the CESS.

5 Future Prospect

In the future, complex systems and their simulation methods show the following development tendencies:

(1) New complex systems will emerge.

For example, the COVID-19 pandemic[108–110] is a novel complex system, which has most of the characteristics of complex systems. Its outbreak began in 2019 and has killed millions of people. On January 30, 2020, the World Health Organization declared it as a public health emergency of international concern. People all over the world are still fighting fiercely against the COVID-19 pandemic. Notably, scientific research workers are working hard to research treatment methods and vaccines.

(2) The idea of complex systems will bring new applications.

Some experts have applied it to economics. For example, SFI established the artificial stock market model with the viewpoint of complex systems for the stock market. Some scholars have applied complex systems to education. Focusing on the problem of continuous learning of students, Forsman et al.[111] discussed the feasibility of using complexity science as a framework to expand the application of the physics education research method. They found that building a social network analysis from the perspective of complexity science provides new and powerful applicability to a wide range of physical education research.

(3) The fusion of multidisciplinary knowledge will be an important means to discover complex systems.

Complex systems themselves often involve multiple disciplines. Consequently, we can make full use of the knowledge accumulation derived from multiple disciplines and integrate them to form a new processing mode. This improvement is of great significance to the discovery of complex systems.

(4) Novel intelligent technologies will be constantly emerging.

Novel intelligent technologies provide new strategies for the research of complex systems. For instance, refined intelligence is a newly proposed intelligent technology by Zheng et al.[31], which forms a new generation of artificial intelligence theory on the strength of complexity and multiscale analysis.

(5) Other meta-synthesis methods have been proposed.

Due to the characteristics of complex systems, they cannot be dealt with in just one way. Therefore, the integration of multiple approaches is often required. For example, the hall for seminar systems; the simulation method combining an artificial system, computational experiment, and parallel system; M-Space and M-Interaction; and M-Computing are all examples of method integration. Hence, meta-synthesis methods are effective methods to discover complex systems.

(6) The development of complex networks will improve the study of complex systems.

From their inception, complex networks have received surprisingly great attention. Complex networks[112] will remain a mainstream of complex system models for a long time. Complex networks always represent a high academic ground of complex system models.

Figure 10 presents an illustration of future prospects in this field.

6 Conclusion

In this study, the development history of complex system research is summarized, and the common characteristics of most complex systems are presented. Then, the simulation methods of complex systems are introduced in detail from four aspects, namely, meta-synthesis methods, complex networks, intelligent technologies, and other methods. From the overall point of view, intelligent technologies are the driving force, and complex networks are the advanced structure. Meta-synthesis methods are the integration

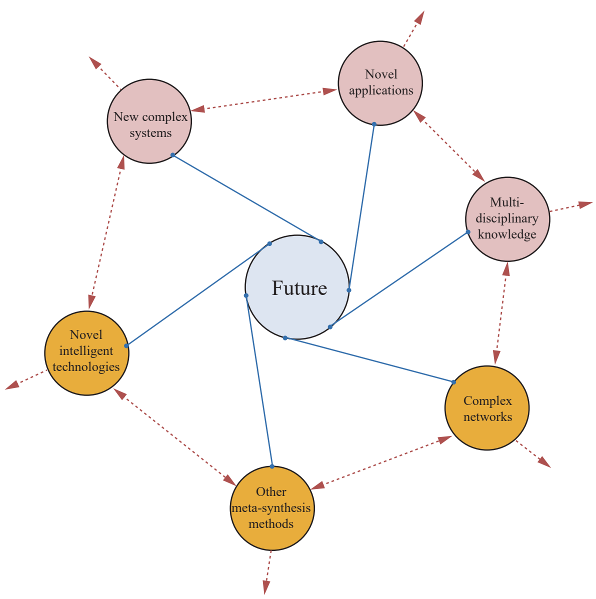


Fig. 10 Illustration of future prospects.

strategies, and other methods are the supplements. Taking digital reactor simulation, simulation of logistics system in industrial sites, and crowd evacuation simulation as three examples, we explain in detail how to apply simulations to study complex systems. The examples show that simulations are a useful means and important method in complex system research. Finally, future development prospects for complex systems and their simulation methods are discussed.

In the future, we will further explore the characteristics of complex systems. Based on the study on typical complex systems, we will propose new simulation methods to deal with complex systems.

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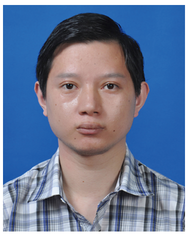

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