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Exploration and Exploitation of New Knowledge Emergence to Improve the Collective Intelligent Decision-Making Level of Web-of-Cells With Cyber-Physical-Social Systems Based on Complex Network Modeling

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ABSTRACT Through exploration and exploitation of new knowledge emergence, the collective intelligent decision-making (CID) level of Web-of-Cells (WoC) proposed by ELECTRA will be dramatically improved. For this purpose, we thoroughly investigate complex network theory and modeling methods for WoC with cyber–physical–social systems (CPSS). WoC is a new intelligent dispatching framework characterized by weak centralization, self-organization coupling, high independence, efficient coordination, and autonomous learning. Based on these characteristics and actual engineering demands, in this paper, we adopt complex network theory, parallel machine learning, and multi-agent stochastic game theory to address three basic scientific issues in WoC dispatching and control: how to build a complex network model for WoC with CPSS to stimulate new knowledge emergence; how to analyze the evolution structure stability and operation stability during this knowledge emergence process; and how to use the emerged new knowledge to achieve cell autonomy and system-wide coordination based on independent and CID, respectively. Finally, we conduct some explorations and make a prospect for WoC. The biggest innovation of this paper lies in thoroughly investigating how to fully stimulate and utilize new knowledge emergence from WoC to greatly improve its CID level of dispatching and control. This will be of great significance to the development of new-generation power system smart dispatching in the future.

INDEX TERMS Web-of-Cells, exploration and exploitation, new knowledge emergence, collective intelligent decision-making, complex network theory, parallel machine learning, multi-agent stochastic game theory, cyber-physical-social systems, cell autonomy, system-wide coordination, smart grid, dispatching and control, ELECTRA.

I. INTRODUCTION

With a rapid development of global distributed renewable energy resources in recent years, China has made remarkable achievements in the development of renewable energy. According to the new energy plan, the wind power and solar energy in China will reach more than 210 million kW and 110 million kW by 2020, respectively [1]. At present, China promotes the development of renewable energy through market means, and vigorously promotes the development of distributed energy via demonstration projects such as micro-grids and new energy demonstration cities, ensuring that non-fossil energy accounts for 15% and 20% of primary energy consumption in 2020 and 2030, respectively. From a development perspective, the global energy structure is also undergoing profound changes. In the future, global energy consumption will be dominated by renewable energy.

The International Energy Agency predicted that the proportion of global clean energy will exceed 30% in 2030 [2]. Moreover, an obvious crowding-out effect has been produced on traditional power supply due to a high permeability of the distributed generation (DG) with features of intermittency and random nature, thereby the global power systems are gradually confronted with a new challenging issue [3]–[7], i.e., what is the form of the dispatching and control system of electric power systems in the case of high-penetration DG participating in the free transactions of electricity market (EM) in the future?

To address it, many scholars have carried out a prospective work regarding this future scenario [5]–[15]. Since the marketing and social factors will remarkably enhance the complexity of the power systems, traditional power system analytical approaches and mentalities are difficult to be competent. Hence, it is essential to carry out basic investigation work from the perspective of complex systems, especially complex network theory. In this paper, we try to answer this issue via investigating how to improve the dispatching and control level of a class of complex systems—Web-of-Cells (WoC) with cyber-physical-social systems (CPSS) based on self-organization coupling and collective intelligent decision-making (CID) capabilities—through the exploration and exploitation of new knowledge emergence. Here, WoC is a novel idea of weak-centralization intelligent dispatching and control framework proposed by the European Liaison on Electricity Committed Towards long-term Research Activity (ELECTRA) in 2015, and it is also the primary research object in this paper.

Before the WoC was put forward, in order to fully cope with high-penetration renewables in smart grid, a new hot research area has been formed on improving the capabilities of electric power systems to optimize, dispatch, and control DG. Further decentralization of energy management system (EMS) becomes a major solution. In particular, traditional centralized-control power system EMSs are allocated to the distribution network bottom layers.

Concretely speaking, in 2010, the China State Grid and China Southern Power Grid began research and construction of intelligent dispatch system architecture. In 2011, Q. Lu, an academician of the Chinese Academy of Sciences, together with other researchers jointly proposed concept and framework of power system smart wide area robot (called Smart-WAR) [16]. In 2013, Sun *et al.* [17] systematically proposed an EMS Family thinking—decentralized autonomy and centralized collaboration—for the power systems in the National Key Basic Research Development Program (i.e., 973 Program). In 2014, we have proposed the concepts of territorial power grid and frequency autonomy in the National Natural Science Foundation of China (NSFC) Program. Subsequently, in 2015, the ELECTRA Integrated Research Programme (ELECTRA IRP) [3] put forward the novel concept of WoC and control scheme for the future (2035+) power system with high-penetration renewables for the first time. Moreover, in 2018, the National Smart Grid Joint Foundation of China Guide states that it focuses on supporting research on the fundamental issues of a new generation of power systems that are widely interconnected, intelligently interactive, smart and flexible, and securely controllable.

Now, we briefly introduce the connotation and development process of the research object in this paper —WoC as follows. This conceptive WoC is a completely new power grid dispatching framework and also a forward-looking research result after a long-term investigation on smart grid, as illustrated in Figure 1. WoC is proposed to enable the future power system to fully cope with high-penetration renewables in power grid. Therefore, the precondition of WoC construction is to predict the future development and change trends of the power grid through scenario hypothesis, which is also an important basis for this forward-looking system [18].

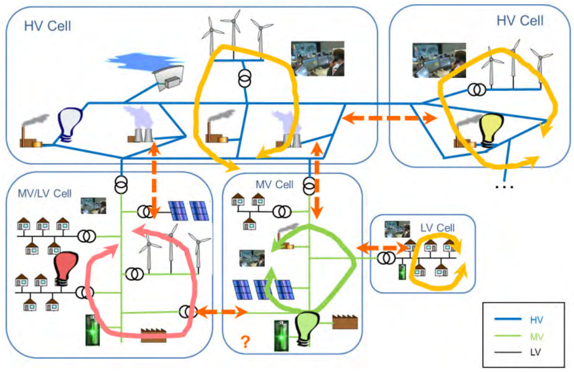


FIGURE 1. Illustration of the novel weak-centralization WoC proposed by ELECTRA in [20].

Based on investigations conducted by E-highway 2050 [19], ELECTRA has extracted seven uncontroversial development trends [20] in the future power system as follows: i) power generation will shift from classical dispatchable units to intermittent renewable energy; ii) power generation will shift from few large units to many smaller units; iii) power generation units will substantially shift from central transmission system connected generation to decentralized distribution system connected generation; iv) electricity consumption will increase significantly; v) large amounts of fast reacting distributed resources can offer reserves capacity; vi) electrical storage will be a cost-effective solution for offering ancillary services; and vii) ubiquitous sensors will vastly increase the power system's observability.

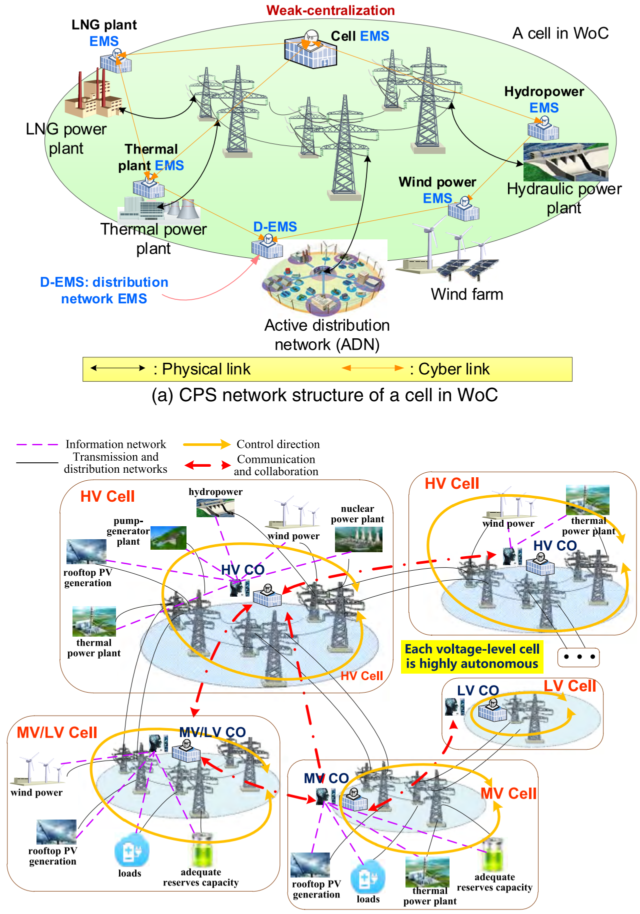
ELECTRA also deemed that [20] developments in information and communication technologies would support the pathway towards more decentralized managed power systems.

As depicted in Figure 1, ELECTRA defines the cell in WoC [3], [4] as a flexible combination of interconnected distributed generators, energy storage units and loads, within a certain range of power/geographical boundaries. In WoC, future power system (grid) will be divided into many smaller entities (geographical areas), i.e., cells, with local observability and control by a cell operator (CO) that is responsible for the real-time control of the cell. Among the cells, each one has autonomy, and the control relationship between them is equivalent. Therefore, local problems are solved locally in a secure manner, without system-wide communication, bottom-up aggregation and central decision making [20]. More importantly, the cells in WoC are connected with each other via tie-lines (one or multiple, radial or meshed), ensuring that neighboring cells can support each other in an autonomous distributed collaborative way and decide on local activation optimization [20]. In addition, ELECTRA proposed that [20] cells can contain/span multiple voltage levels, including high-voltage level (HV), medium-voltage level (MV), and low-voltage level (LV); are dimensioned in relation to computational complexity of detection and resolution, sufficient reserves providing resources, etc.; and do not need to be self-reliant for matching demand with supply.

In Figure 1, the primary system architecture of the power system has not been changed substantially in WoC. However, it has a significant difference in operation and control modes. Therefore, from the perspective of actual dispatching and control situations of power systems, WoC is a novel weak-centralized cyber-physical framework (see Figure 2a) with self-organization evolvement and CID characteristics. After taking into account social factors in WoC, such as complex game relationships (e.g., Stackelberg game, general Nash game) between cell operators with different voltage levels (e.g., HV CO, MV CO, LV CO), which means multi-stakeholder conflict of interest (i.e., the overall interests of multiple stakeholders such as power suppliers, power distributors, and industrial, commercial and residential users are difficult to coordinate); thus the cyber-physical systems (CPS) integrated WoC will be transformed into CPSS integrated WoC (see Figure 2b).

As demonstrated in Figure 2, we can further conclude that the WoC proposed by ELECTRA is a weakly centralized intelligent dispatching and control framework for the next generation of power systems. The difference between WoC and current power systems in terms of dispatching and control is briefly introduced as follows. Generally speaking, current power system dispatching and control is based on a transmission operator (TSO) and distribution operator (DSO) mode, called TSO-DSO mode, through which the entire power system management is implemented hierarchically. This TSO-DSO mode is a typical strong centralized control mode, which ensures a safe and stable operation state for the power grid. In contrast, as demonstrated in Figure 2a, the dispatching and control idea of a cell WoC is to decompose current power system EMS into multiple autonomous individuals with simple structure and functionality. Moreover, for the entire WoC system, as depicted in Figure 2b, where multiple cell operators with different voltage levels such as HV CO, MV CO and LV CO coordinate mutually, especially neighboring coordination, to achieve overall optimal dispatching and control.

Therefore, based on effective and real-time information communication and mutual coordination between cells and



(b) CPSS network structure of the entire WoC

FIGURE 2. Illustration of the self-organization network framework of WoC, where (a) demonstrates the control mode of a cell in WoC, which is typical cyber-physical network framework; and (b) presents the overall framework of WoC containing multiple cells with different voltage level, which is a cyber-physical-social network structure due to the consideration of social factors, such as the game relationships between different cell operators in the context of an open EM.

their neighbors, the coordinated optimization and stability control of the entire system is achieved. The dispatching and control of WoC is a typical distributed coordinated control framework with cell as a basic unit [20]. At this point, a cell in WoC refers to a flexible combination of interconnected distributed generators, energy storage units and loads within a certain range of electricity or geographic boundaries; moreover, within each cell, there is sufficient active reserve capacity and reactive compensation capacity for voltage and power balance control. This cell unit-based distributed control structure adopts a thinking of weak-centralization, which is similar to the idea of current micro-grid [4].

In terms of dispatching and control, Table 1 presents a detailed technique comparison between current power system and WoC in terms of dispatching and control, including architecture characteristic, power sources structure, control modes and system modeling methods, dispatching and control capabilities of the new energy, supporting capabilities of the EM, and demand response (DR) models, which are as follows.

TABLE 1. A technique comparison between current electric power system and WoC system in terms of dispatching and control.

Technical features		Current electric power system	WoC system proposed by ELECTRA [3]
Architecture characteristic		Strong-centralized	Weak-centralized
Power sources structure		Dominated by large-scale power sources such as hydropower, thermal power, and nuclear power	High-penetration new energy resources
Control modes	Stability control	Mainly centralized control via sectional control	Mainly decentralized control (boundary control)
	Load balancing control	Mainly system-wide cross-regional balancing	Mainly cell internal balancing
	Primary and secondary networks coordination control	Leader-follower mode is dominant, reflecting simple features	Independent mode is dominant, reflecting flexible features
	Islanding control	Planned islanding mode, reflecting not flexible features	Adaptive islanding mode in the cell, reflecting flexible features
System modeling methods		Deterministic simple system modeling method	Stochastic complex system modeling method
Dispatching and control capabilities of the new energy	Span of dispatching and control capability	Large new energy power station	Large new energy power station Distributed generation
	New energy consumption capability	Weak	Strong
Supporting capabilities of the EM	Transaction entity	Simple stakeholders	Complex stakeholders
	Transaction mode	Collective transaction	Collective transaction and inter-neighbor transaction
	Transaction type	Single mode	Flexible and varied modalities
DR models	Load control mode	Breaking heavy load	Supporting massive small load control
	Response mode	Centralized mode	Centralized mode and inter-neighbor mode

Based on Table 1, Figure 3 provides a more vivid comparison for the difference of dispatching and control between current power system and the weak-centralization WoC proposed by ELECTRA.

In fact, the weak-centralization dispatching and control framework adopted by WoC can be regarded as a generalized systematization of micro-grid framework. As illustrated in Figure 3, the WoC dispatching and control structure is more powerful than available centralized hierarchical dispatching and control systems in aspects of system orderliness, flexibility, extensibility, reusability, and compatibility. Therefore, WoC is very consistent with the technical requirements of a new generation of power system architecture, such as widely interconnected, intelligently interactive, flexible and smart, safe and controllable; thereby WoC will be more suitable for new-generation energy and electric power systems with high-penetration renewables.

Moreover, Figure 3 shows that the cell in WoC is the smallest and autonomous unit or individual, so that the fully-distributed control and communication can be achieved through interaction between individuals, as well as interaction between individuals and the environment. Compared with current power grid dispatching and control, Table 1 indicates that the intelligence level and supporting ability of the EM are greatly improved in WoC dispatching and control system, as well as the control and consumption capability of distributed new energy. Moreover, the entire WoC system has significant advantages in self-organization, independent decision-making, collective coordination, and autonomous learning, which are as follows [4]:

- Self-organization coupling characteristic. The global structure of WoC is presented by the interaction between cells, especially between neighbors. The interaction rules are only relied on local information and inter-neighbor information, instead of global information.
- Highly independent decision-making capability. The control of WoC is occasionally relied on central control, thus each cell in WoC system has basically equal status, and the state of them does not directly affect the whole system.
- High-efficiency collective coordination capability. Each cell relies on limited information sharing and interaction between neighboring cells to achieve collaborative optimization, which is originally performed depending on the centralized control of a center.
- Autonomous learning capability. The internal control of each cell is realized by feedback, so it has capabilities of adaptation and optimization.

Therefore, although the rules of each CO are simple, the WoC system is a clusterability-based result of organizational effect and structural effect. Moreover, the higher the overall effect level, the more intelligence the group knowledge will emerge. The control idea of WoC is to

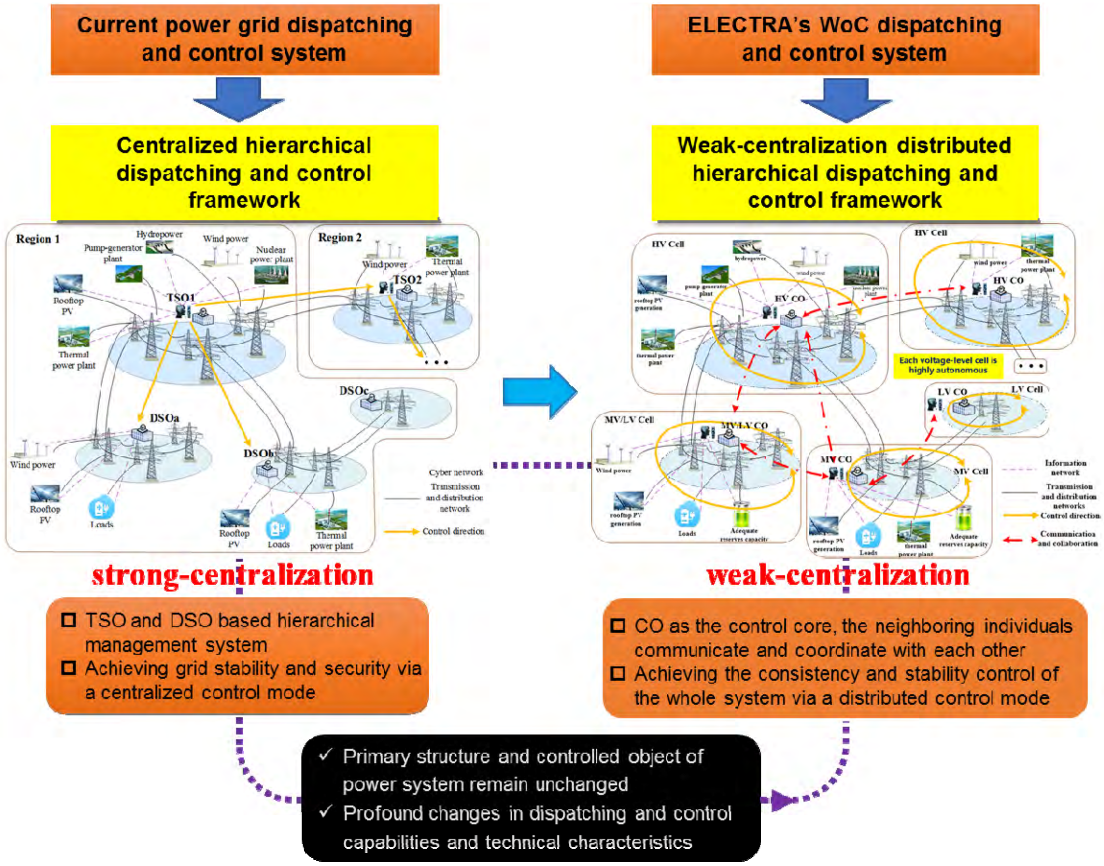


FIGURE 3. Illustration of the essential differences between current power grid dispatching and control system and WoC dispatching and control system. Here, current power grid dispatching and control system is strongly centralized and hierarchical, in contrast, the WoC dispatching and control system framework is weakly centralized and distributed.

transform the intelligentization of power system into swarm intelligence to provide a platform and an opportunity for the continuous emergence of group knowledge. Hence, it is of great significance to the development of power system intelligent dispatching and control and the research on utilization of renewables in the future.

In a word, WoC is essentially a decentralized autonomous power grid in which massive and weakly-controllable DGs are dominant. Therefore, the fundamental changes in power supply structure, system inertia, and information interaction are bound to profoundly to facilitate the transformation of traditional control modes of power system [5]. Taking the power systems in China for an example, in the past, relying on the dispatching of dozens of large power plants, a provincial power grid is able to complete basic power balance and electricity balance control of the power system [21]. Currently, after large-scale generation units are forced out by massive distributed power sources, especially massive DG system operators are participating in free market transactions, resulting in that the power balance and electricity balance of large-scale power grids need to be relied on massive and uncertain DG sources. This has become an enormous challenge in China.

Therefore, although the concept of WoC was proposed by ELECTRA in 2015, it is still at a conceptual and technical framework stage. Actually, many new challenges have been put forward regarding WoC in study of fundamental theories and specific techniques. The construction and application of the intelligent dispatching and control system in WoC needs to tackle a series of dispatch optimization and decision-making issues after the weakly-centralized interconnection of cells in WoC. Among them, the biggest challenge or the most significant technical problem needs to be tackled urgently is how to greatly improve the CID level of WoC dispatching and control system. That is also the focus of this paper.

Therefore, the core issue investigated in this paper is how to greatly improve the collective intelligent decision-making capability to achieve global optimal dispatch and control for a class of complex systems—WoC—relying on massive autonomous cells with limited information, weak controllability, small capacity, and wide distribution. To address it, we need to rely on multidisciplinary approaches and cutting-edge techniques, so that we can explore solutions to such issue from basic theoretical investigations, as shown in Figure 4.

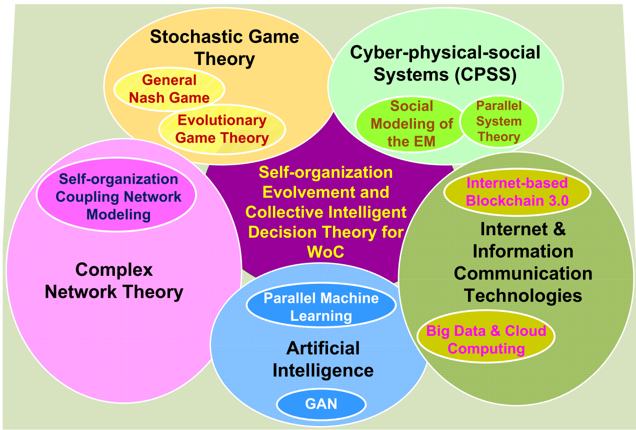


FIGURE 4. **The major relevant theories and technologies involved in key scientific issues investigation for the weakly centralized WoC in this paper.**

Based on Figure 4, we aim to develop an intelligent dispatching and control system as ultimate goal in the context of high-penetration distributed renewables integrated. For the first time, we systematically put forward investigations regarding key technologies to improve the CID level of dispatching and control for WoC. Aiming at technical characteristics of WoC, such as self-organization coupling, highly independent decision-making, high-efficiency collective coordination, and autonomous learning, as well as actual engineering demands for WoC, we adopt advanced theoretical approaches and mathematical tools such as CPSS [22], complex network theory [23], parallel machine learning (PML) [9] and evolutionary game theory (EGT) [6] to concentrate on a critical issue: how to use huge numbers of cells in WoC with features of limited information, weak controllability, small capacity, and wide distribution achieve new knowledge emergence to greatly improve the CID level of WoC in optimal dispatching and control. Therefore, we systematically propose to investigate four key scientific issues as follows:

i) How to use complex network theory to model the WoC with CPSS deeply integrated, self-organization coupling, and CID features to stimulate new knowledge emergence?

ii) How to use EGT and other theories to analyze the evolution structure stability and operation stability during the process of new knowledge emergence?

iii) How to use the new knowledge emerged in WoC through complex network modeling to achieve cell autonomy based on independent intelligent decision-making?

iv) How to use the new knowledge emerged in WoC through complex network modeling to achieve system-wide coordination among cells based on collective intelligent decision-making?

To tackle the issues above, we strive to seek innovative breakthroughs at the intersection of complex network theory, multi-agent stochastic game theory and collective machine learning (ML) to generate emergence phenomena of collective intelligence and group new knowledge, noticeably improve the CID level of WoC in complex system circumstances, and to explore system development and engineering project implementation, expecting that engineering verifications are able to be conducted in small-scale intelligent dispatch engineering demonstration projects.

The major engineering value and scientific significance of this paper can be summarized as follows:

i) We construct a self-organization coupling complex network with deeply integrated CPSS for WoC to stimulate new knowledge emergence, which can greatly expand the collective intelligent learning space of WoC. This is a new knowledge exploration stage, in which the self-organization coupling characteristics of the WoC determine that the complex network topology dynamic laws must be investigated combining with the intelligent system dynamic behavior caused by disturbance. This is a research work to be conducted in the power system field for the first time. We can use this complex network modeling to stimulate new knowledge emergence in WoC, thus greatly expanding the collective intelligent learning space for the cells in WoC.

ii) We thoroughly investigate the PRL method and multi-agent stochastic game theory, based on which, the emerged new knowledge is able to be fully utilized to greatly improve the CID level of WoC. This is a new knowledge exploitation stage, in which the PRL and multi-agent stochastic game theory are employed to construct a complex CPSS-based parallel system for WoC. This research work is the first time to be conducted in the smart grid field, thus it not only has high research difficulty, but also can make full use of new knowledge emerged in complex smart grid to greatly improve the intelligent decision-making level of the group cells in WoC. Moreover, the results achieved in this paper can be used in some small-scale intelligent dispatching demonstration projects (e.g., intelligent dispatching robot project) in the future, thus indicating important engineering application value and guiding function in the field of energy and electric power system intelligent dispatching and control, especially smart grid and Energy Internet fields.

This paper is structured as follows: in section II, we first briefly depict the key techniques used for WoC research in this paper. Subsequently, based on a variety of advanced theoretical tools, four basic scientific issues of the WoC, i.e., complex self-organization coupling network modeling for new knowledge emergence in the WoC integrating CPSS; evolution structure stability and operation stability analysis during the process of new knowledge emergence; cell autonomy in WoC based on independent intelligent decision-making; and system-wide coordination among cells based on collective intelligent decision-making, are thoroughly investigated in Sections III, IV, V, and VI, respectively. Moreover, some explorations on system development and engineering practice of the WoC are carried out in Section VII. In Section VIII, we make a brief summary of the main investigations in previous sections as well as a prospect for the future development of WoC. Finally, Section IX concludes the main innovations of this paper. The logical relation between Sections III, IV, V, VI, and VII in this paper is demonstrated in Figure 5 as follows.

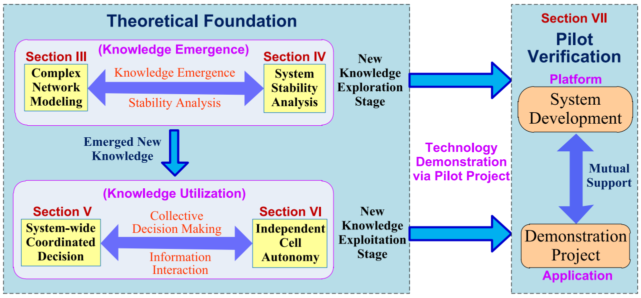


FIGURE 5. Logical relation between Sections III, IV, V, VI, and VII in this paper.

II. KEY TECHNIQUES USED FOR WOC

In recent years, the technological development of smart grids at home and abroad has been further accelerated, which is mainly reflected in four aspects of power source, network, load, and energy storage. These four aspects are undergoing profound changes. In 2015, aiming at the future (2030+) power system with high penetration of renewable energy resources, ELECTRA proposed based on the scenario research conducted by E-highway 2050 [19] and extracted seventh incontrovertible development trends in the future power system [18]–[20]. Faced with a shift relationship between traditional and distributed power supply, how to effectively facilitate the massive interconnection of distributed power supply is an important part of the development strategy of various countries' energy and power in recent years. ELECTRA proposed the concept of WoC for the first time for power systems that are highly permeated by renewable energy in the future. WoC is a weakly centralized, distributed and hierarchical smart grid new dispatching framework, indicating that the role of the superior CO that dispatches and controls all cells in WoC is greatly weakened.

This weakly-centralized WoC framework can be regarded as an entire systematization of the micro-grid architecture. The emergence of this inspiration is not only driven by the actual demand for smart grid technology development, but also inextricably linked with latest research improvements in some key techniques, including Internet techniques (e.g., Internet-based blockchain (IBC) technique based a decentralization thinking), complex network theory, collective ML technique (especially PML), and multi-agent stochastic game theory, as demonstrated in Figure 4. These key techniques are introduced as follows.

A. INTERNET TECHNIQUES

WoC is highly consistent with the technical development trends of the decentralization thinking in IBC. Under the impetus of Internet techniques, human communication has undergone profound changes. New communication and data analysis techniques have emerged in an endless stream. Power systems are also becoming truly digital power systems. Currently, big data and cloud computing technologies have gradually become a mainstream direction for the development of energy and electric power systems. Although the investigation on these technologies has extremely high requirements on dispatching operation data and communication security, the power departments throughout the world have been actively carrying out research work on how to use the open public Internet and multi-source data fusion methods to enhance the analysis capabilities of the system.

In recent years, the development of power system in China has also begun to accelerate rapidly in the direction of market-oriented reforms. With the tempting prospects of day-trading of power, incremental distribution network opening, distributed power supply online trading, and ancillary services of EM, the technology of IBC that combines Internet and market finance has begun to receive sufficient attention in the power industry [24]. The IBC technique can be regarded as a high-level form of big data technique, and now it has been developed into IBC 3.0 with a wide application [25], [26]. The decentralization idea of IBC 3.0 coincides with the dispatching model of WoC, but this is definitely not a coincidence with a small probability. In our viewpoint, the information system decentralization is an inevitable choice in Industry 4.0 era. The idea of decentralized autonomy and centralized collaboration of the power system EMS proposed by Sun *et al.* [17] is essentially the same as the WoC ideology. However, it must be emphasized that the weakening effect of WoC on traditional centralized control centers is much higher than that of new EMS architecture proposed in [17]; moreover, WoC is closer to the idea of decentralized IBC 3.0. Therefore, the technical challenges from WoC are also more arduous.

B. COMPLEX NETWORK THEORY

The complex network theory [27], [28] is included in complex system theory, and it is a basic mathematical tool that can be used to stimulate new knowledge emergence in the WoC, which is characterized by self-organization evolvement and CID characteristics. Concretely speaking, the complex system consisting of intelligent groups interacts continuously. This is a process of individual linearity evolving into overall nonlinearity. In this process, the group characteristic, nonlinearity characteristic and complex system characteristic will emerge in a relatively stable stage. These emerged new features can be extracted as new knowledge through group ML. That is the process of new knowledge emergence from complex systems. The complex systems here are defined by two assumptions as follows:

i) Inseparable assumption. In essence, the entire behavior of a complex system cannot be completely determined by a separate analysis of its partial behavior relative to any limited resource;

ii) Agnostic assumption. In essence, the overall behavior of a complex system cannot be completely determined in advance in a large scope relative to any limited resource.

Therefore, complex system theory emphasizes the method of combining holism and reductionism to analyze systems, uses individuals and their interactions or uses evolutionary structures to describe systems, takes the overall behavior of the system (such as emergence) as the main research target and description object, and finally discusses the evolutionary dynamics of the system such as power-law distribution, self-organized criticality. That is why we adopt complex system theory, especially complex network theory, to model the self-organized coupling WoC with CPSS deeply integrated. Typical complex network models include rule network, small world network, random network, and so on, as illustrated in Figure 6.

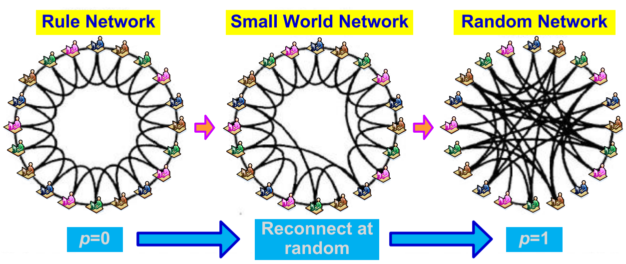


FIGURE 6. Illustration of some typical complex network models, in which p is the degree of random reconnection ($0 \leq p \leq 1$), representing that the higher this random reconnection degree, the more complex the structure of the network.

The development of complex network theory is briefly introduced as follows. In the 1960s, Hungarian mathematicians Erdo and Renyi established random graph theory [29], which was treated as the pioneering systematic research work of complex network theory in mathematics. Since the late 1990s, after Watts and Strogatz [30], Barabási [31] proposed the small world and scale-free network models in *Nature* and *Science*, respectively, the investigation on complex networks has entered an epoch-making research boom. Among them, the stability and synchronization of complex network topology has become one of its main research directions [32]–[40]. For many dynamic networks in real world, the failure of links or emergence of new links occurs in network from time to time, due to the links of nodes in the network are not always stable, and moreover, thus the structure of the network will change dramatically, and it is inevitable to fact switching between some different network topologies. For this reason, The Markov switching theory was proposed for the first time by Krasovskii and Lidskii [41] in 1961 mathematically to describe the randomness of switching between different models.

In recent years, the dynamic analysis issues of complex networks with Markov switching features [42] have stimulated the interest of research in the international academic community. The application of this research in the social, biological, and engineering fields is in the ascendant. In addition, complex network theory has been used to investigate the issues of power grid, which is mainly focused on three aspects [43]–[48]: network structures, correlation between network structure and network performance, and comprehensive application. These have made important progress in topology modeling, cascading failure model, vulnerability analysis and key unit identification. The smart grid under the open EM is obviously a complex network. Therefore, it will be an inevitable trend to analyze issues of such a complex network based on complex network theory. This is a systematic theory that combines holism and reductionism as a main mathematical analysis method.

From the perspective of self-organization coupling characteristic of WoC, Markov switching dynamic network models can be used as a powerful mathematical tool for its network modeling. On this basis, Markov Decision Process (MDP) can also well solve related mathematical modeling issues of WoC in ML. In a word, the introduction of complex network theory into WoC is expected to fully utilize complex systems to stimulate the emergence of new knowledge in WoC via self-organized coupling and evolving. An example is provided here to explain the phenomenon of knowledge emergence as follows. A solution for a robot to achieve a certain goal can emerge by the robot itself from a cognitive process, and then it can respond to the external environment under the guidance of external information acquired by simple sensors to accomplish specific tasks, thus allowing the robot to handle unpredictable dynamic changes in the environment, which is very common in space missions. Therefore, through exploiting the new knowledge emerged from the WoC, we can greatly improve the CID level of WoC, especially the aspects of dispatching and control.

C. COLLECTIVE ML METHODS

Collective ML methods [49]–[51] are critical to greatly improve the CID level of WoC. ML is completed necessarily based on a good knowledge representation system. In the past 30 years, great progress has been made in ML [52]. The deficiencies in the traditional theoretical framework of ML are being gradually discovered and confirmed. Thereby, new theoretical frameworks for ML have been proposed [53]–[56]. In 2015, the extremely influential investigations from Google's DeepMind team were published in *Nature* [57], [58], which made the deep reinforcement learning become a hot topic in artificial intelligence (AI) community. Based on deep reinforcement learning method, a Go program, named AlphaGo, was developed by this team in 2016 and it broke the myth that Go cannot be simulated by AI. As a result, the multi-layer artificial neural network (ANN) based deep learning as a perception and the MDP-based reinforcement learning as a decision form a golden combination of ML [58], [59]. In 2017, Li *et al.* [54] proposed a theoretical framework of PRL based on parallel system theory. In this framework, a parallel virtual artificial system is employed to generate huge numbers of virtual samples for ML. In addition, generative adversarial network (GAN) [60]–[62] can be employed to automatically generate a large amount of simulation model data by constructing a max-min adversarial gaming system containing a generator and a discriminator (see Figure 7), which largely solves the small sample size problem in real circumstances.

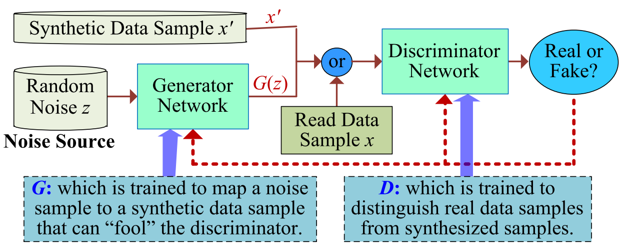


FIGURE 7. The computing flow and structure of a GAN, in which the main idea of GAN is to build a zero-sum game to achieve learning through the confrontation between two players, i.e., a generator and a discriminator. The former is mainly used to generate samples and try to make them consistent with the training samples. The purpose of the latter is to accurately determine whether the input sample belongs to the real training sample. Therefore, the generator and the discriminator are learned during the training process for a GAN, and typically implemented with neural networks.

From AlphaGo [58], AlphaGo Zero [59], AlphaZero [63], parallel system [54], [64] to GAN [60]–[62], researchers have found ways to obtain data samples with sufficient capacity for ML. Obstacles that hinder the improvement of intelligence level of ML are gradually being removed. ML has been moved from the known training sample set (i.e., limited small data) to the new era of massive hypothetical training samples (i.e., unlimited big data) obtained via self-exploration, which will be a watershed for AI to surpass human intelligence. In the field of power systems, there was a research boom in the application of early ML such as back propagation neural network (BPNN) [65], support vector machine (SVM), and fuzzy sets in the 1990s [66]. In the last two decades, the reinforcement learning algorithms [66]–[68] based on MDP as its rigorous mathematical foundation has become a new breakthrough in the field of ML. Among them, Q-learning [69], multi-agent correlated equilibrium Q(λ) learning, and adaptive dynamic programming (ADP), as well as other classical reinforcement learning algorithms have been introduced into the field of power system by the authors [70]–[76].

D. MULTI-AGENT STOCHASTIC GAME THEORY

Multi-agent stochastic game theory, especially EGT, provides a powerful mathematical analysis tool for analyzing the interactions between cells in the weakly centralized WoC. Game theory was formally adopted as a theory, beginning with the work conducted by Von Neumann and Morgenstern [77] in 1944. Nash then proposed and discussed the important concept of Nash equilibrium from 1950 to 1953 [78]–[81], which laid the theoretical foundation for non-cooperative games. Classical game theory is based on three basic assumptions [82]: 1) players in the game are completely rational; 2) players have common knowledge; and 3) game structure and game environment are given in advance. Obviously, these assumptions are difficult to be satisfied in a complex system environment. In order to break the restrictions of the above three principles, Smith and Price introduced evolutionary ideas in biological theory into game theory, and published a creative paper *The Logic of Animal Conflict*[83] in 1973. This kind of game analysis methodology is originated from biological evolution theory, called evolutionary game theory (EGT), which is considered as a modeling method suitable for solving dynamic game issues in networks. In network groups, the transmission of information and the selection of strategies in evolutionary games can all be seen as the dynamics behavior on the network that obeys certain laws. How to characterize this dynamics behavior and discover the mechanism of it is the focus for researchers [84]–[87]. After EGT was put forward, it was quickly applied in many fields including power system. The relevant research work in power system is mainly concerned on the power economy fields [88], [89] such as EM game behavior analysis, demand-side management, electricity price and investment, and power grid planning, etc. However, it is a pity that the game agents that have been investigated are mostly simpler two-party game issues.

Furthermore, the weak-centralization WoC includes a very complex multi-agent stochastic game structure, especially a dynamic evolutionary game structure, thus the deep-level evolutionary game mechanisms, evolutionary game paths, and evolutionary game laws of WoC will be very challenging, and meanwhile promising.

III. COMPLEX NETWORK MODELING FOR NEW KNOWLEDGE EMERGENCE

Following contents are investigated in this section. First, we investigate the mathematical relationship between the self-organization behaviors of physical network, cyber network, and social network of WoC and the coupling networks, thus establishing a mathematical model of Markov switching complex dynamic grid (MSCDG) to describe frequent dynamic coupling and switching behaviors of the complex network. Second, we draw lessons from self-organization critical phenomena of human and social group behaviors, to conduct investigation on the influence of social factors on modeling of WoC in the circumstances of EM, and further attempt to investigate the model of deeply integrating existing CPS-based modeling method of smart grids with social factors. Moreover, we investigate the GAN that is suitable for study of the self-organization evolutionary model of WoC and try to build a parallel simulation system for WoC based on the integration of CPSS. Lastly, through the integration of mathematical analysis approaches and simulation methods, we try to investigate the comprehensive modeling theory of cyber-physical-social self-organization coupling networks facing to WoC. Specific investigation contents are presented as follows.

A. HYBRID MATHEMATICAL MODELING OF CPSS-BASED MSCDG

As illustrated in Figure 2b, WoC is mainly composed of three networks: a cyber-network, a power network (also called physical network), and a social network, thus WoC systems are typical CPSS. Based on this, we conceive a comprehensive WoC after considering the social factors. During a long-term evolution and self-organized coupling process, its detailed cyber-physical-social structure (which can be evolved into different complex CPSS networks) is illustrated in Figure 8. Among this conception, the cyber-network is a secondary network which is composed of control and protection information flows. Nevertheless, the power network is a primary electric power network topology, in which multiple cells constitute a complete WoC system, and each cell owns a transmission network and a distribution network inside. Therefore, this network integrates traditional power supply and DG, and is a multi-component independent network

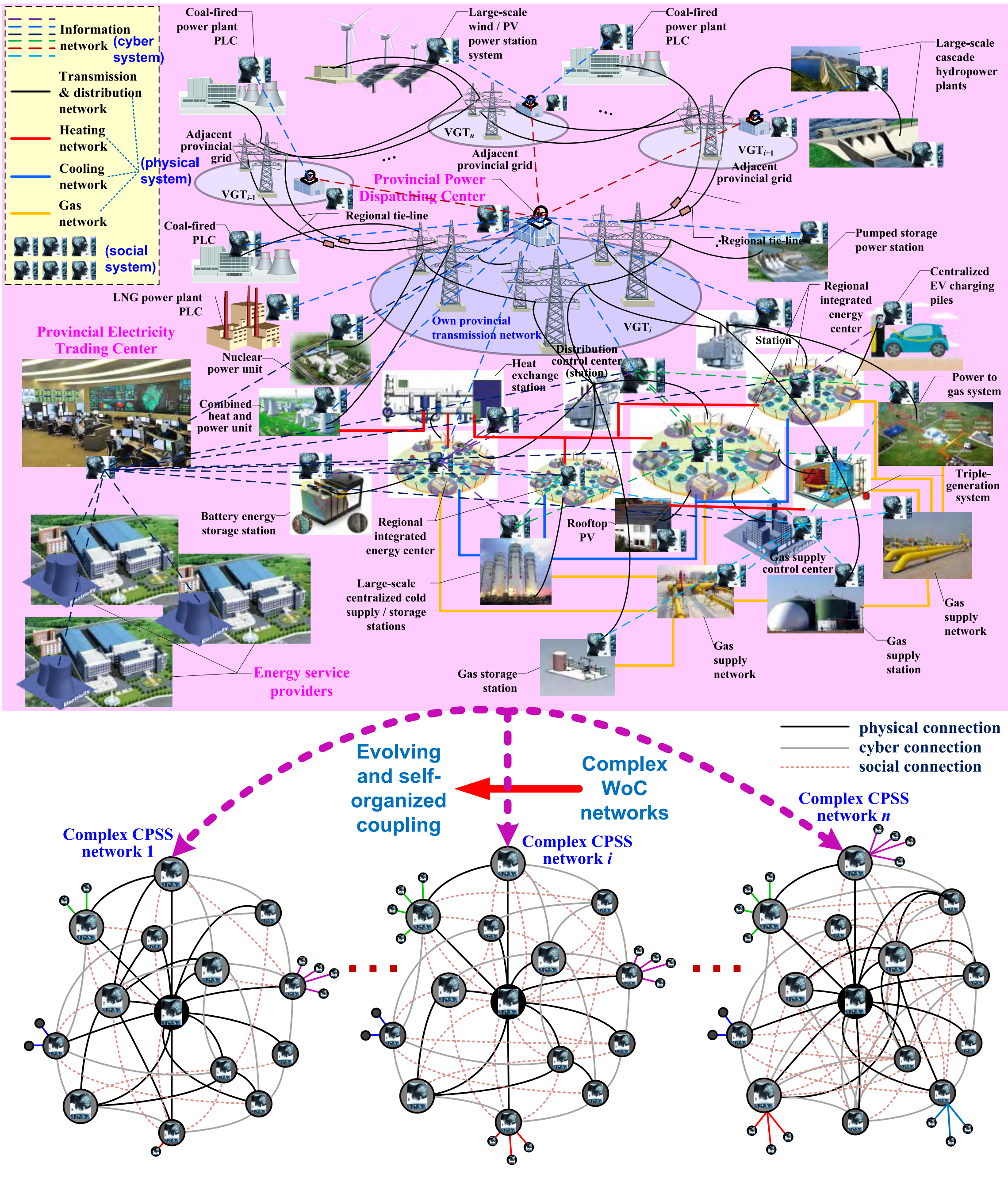


FIGURE 8. Idea drawing of CPSS network structure of WoC, where the figure located above is an ideal drawing of the cyber-physical deep fusion system of WoC, and the figure located below indicates that such cyber-physical WoC can be abstracted to be a complex social network during a long-term evolution and self-organized coupling process when considering the social factors such as difference game relationships between cells, CO behaviors, and transactional relationships between different market stakeholders.

involving power source, network, load, and energy storage. The social network is a game network considering transactions in an open EM, which is constituted by the collaborative/competitive relationships between power dispatching decision terminals. Therefore, it is a relatively abstract social relation network. Moreover, this network is only partially dependent on the cyber-network, so that even if there is no communication and information exchange between cells in WoC, a game relationship can still be formed.

According to the state transition behaviors and interactions continuously occurred in the process of self-organizing and coupling in WoC, we can use the MDP in random circumstances combining with network graph theory to establish its mathematical model. This switched complex dynamic network is a complex dynamics system network containing switching phenomena that arise during the evolving of the network topology structures or states of nodes. In addition, time-delay is a typical feature that exists in the transmission between nodes in the network, thus the time-delay is one of the major causes of network instability and poor performance. Due to the potential application value of Markov switching complex networks in the fields of secret communication, chemical and biological systems, information science and life science, it has become a hot spot with high investigation value. Obviously, the WoC investigated and discussed in this paper fully possesses the above-mentioned characteristics. Therefore, the state transition and network switching phenomena in the complex dynamic network of WoC can be characterized with the MDP or Markov chain. We call a class of dynamic networks with such kind of switching characteristic are a MSCDG [90]–[92]. The network dynamic equation of the WoC can be depicted by the MSCDG based on the following steps.

Step 1: we establish a general mathematical model of complex network consisting of N same dynamical systems which are regarded as nodes of the network. This model is described as

$$\dot{\boldsymbol{x}}_i(t) = \boldsymbol{f}(x_i(t)) + c\sum_{j=1}^{N} a_{ij}\boldsymbol{\Gamma}\boldsymbol{x}_j(t), \quad i = 1, 2, \ldots, N \tag{1}$$

where i is the number of nodes in a network; $\boldsymbol{x}_i(t)$ represents the state vector of the node i; $\boldsymbol{f}(\boldsymbol{x}_i(t))$ is a continuous vector-valued function; $\boldsymbol{\Gamma}$ is an inner-coupling matrix; c represents the strength of coupling; $\boldsymbol{A}_{\mathrm{EC}} = (a_{ij})$ represents an external-coupling matrix of the network topology structure, which is defined as follows: if there is a connection between node i and node j, then it obtains $a_{ij} = a_{ji} > 0$, otherwise there is no connection between them and $a_{ij} = a_{ji} = 0$. Besides, the element on the coupling diagonal is defined as

$$a_{ij} = -\sum_{j=1, j\neq i}^{N} a_{ij}, \quad i = 1, 2, \cdots, N \tag{2}$$

Step 2: we consider that the coupling nodes are non-linear in an actual network, thus there will necessarily be a complex network that is characterized by non-linear coupling. If we further consider that there is a switch function $\boldsymbol{r}(t)$ between different models, thereby the classical complex network model presented in (1) will be transformed into a MSCDG model as

$$\dot{\boldsymbol{x}}_i(t) = \boldsymbol{f}(x_i(t), r(t)) + c\sum_{j=1}^{N} a_{ij}\boldsymbol{\Gamma}\boldsymbol{x}_j(t), \quad i = 1, 2, \ldots, N \tag{3}$$

where $\boldsymbol{r}(t)$ is the transition probability of Markov chain.

Step 3: we need to consider time-delay of this built MSCDG model, due to the speed of information input, transmission and processing is limited in complex network, resulting in a time-delay phenomenon in the network, which will easily lead to instability and performance deterioration of the network system. Thereby, the MSCDG considering time-delay is depicted as

$$\dot{\boldsymbol{x}}_i(t) = \boldsymbol{f}(x_i(t-\tau(t)), r(t)) + c\sum_{j=1}^{N} a_{ij}\boldsymbol{\Gamma}\boldsymbol{x}_j(t-\tau(t)) \tag{4}$$

where $\tau(t)$ is the time-varying delay; and $i = 1, 2, \cdots, N$.

In summary, the MSCDG model elaborated in the three steps above is characterized by continuous time, while such model is required to be a discrete-type one due to many control decisions of power grid are generally discrete in time in practice. Therefore, we can build a discrete-type MSCDG model for the case of discrete decision processes, which is demonstrated as

$$\boldsymbol{x}_i(k+1) = \boldsymbol{f}\,(x_i(k), r(k)) + c\sum_{j=1}^{N} a_{ij}r(k)\boldsymbol{\Gamma}\boldsymbol{x}_j(k) \tag{5}$$

Based on the MSCDG models elaborated above, a mathematical theory analysis can be conducted on the stability and synchronization of the networks in the process of self-organization evolution. The investigation on the stability or synchronization of WoC based on the MSCDG models can be started from the following two aspects. First, starting from the dynamics behavior, we can investigate the stability or synchronization of the networks in order to give the judgment conditions. Second, starting from the network structure, we can judge the synchronization performance so as to improve the synchronization indexes. The investigation of network synchronization issues [93], [94] is mainly based on Lyapunov stability theorem, synchronization manifold, matrix inequality, adaptive control and pinning control, etc., thereby some standards and criteria for determination of network stability or synchronization can be given.

In addition, due to the MDP is also based on Markov chain. Therefore, based on the MSCDG, we are also more convenient to carry out investigations on a class of MDP-based group reinforcement learning methods. The transition probability of the Markov chain, $\boldsymbol{r}(t)$, in (3) can also be solved by the MDP method. This is another important reason why this paper adopts the MSCDG model.

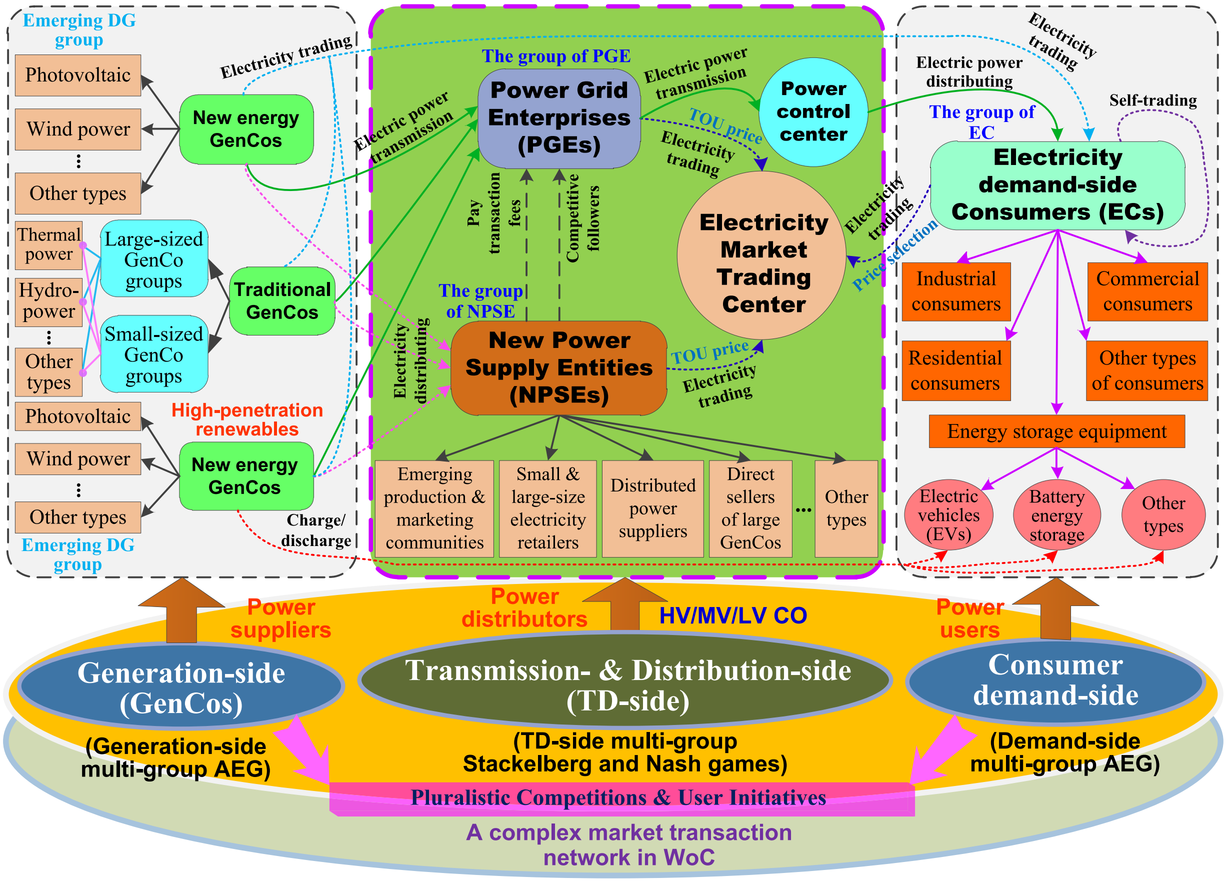


FIGURE 9. Illustration of an open and ever-growing EM framework with complex, diverse, and drastic multi-group evolutionary games of electricity trading involving the groups of PGE, NPSE, and EC.

B. CPSS-BASED PARALLEL SYSTEM SIMULATION MODELING FOR WOC UNDER THE OPEN EM

In China, with a gradual liberalization of EM, in which participants have become more and more complex and diverse, not only including traditional power grid enterprises (PGEs) and electricity consumers, but also together with the emergence of a large number of emerging stakeholders, such as DG, energy storage, controllable load, and electric vehicle (EV), making the electricity trading in the competitive games of EM become more complex, diverse, and drastic, which is illustrated as graphically in Figure 9. These dispatching systems involved in the electricity trading can be seen as different intelligent decision-making agents, thus the group decision-making network formed in the competitive games can be modeled as a social network, which is illustrated in Figure 10 according to [95]. In the Figure 9, the power grid enterprise (PGE) group, new power supply entity (NPSE) group, and electricity consumer (EC) participating in a three-group asymmetric evolutionary game (AEG) in the EM, while the large-sized and small-sized generating corporation (GenCo) groups participating in a two-group AEG.

Based on Figure 10, the modeling of MSCDG is a strict analytical mathematical method. However, for more complicated issues of social modeling, artificial experiment and simulation methods are more commonly used measures to address them, which are also called simulation methods. In 1990, Qian *et al.* [96] proposed a comprehensive integration method based on man-machine combination, indicating that complex system issues should be addressed via integrating expert group decision-making and intelligent information methods. On this basis, we believe that the following investigations need to be conducted: one aspect is study the influence of social and human factors on the modeling of WoC in the circumstances of EM; the other is to investigate the mode and effect of deep integration between existing CPS modeling approaches of smart grid and the social factors, so as to finally build a CPSS-based (i.e., tightly integrating social factors into the CPS) parallel simulation system for the WoC. The specific framework of this parallel simulation system is designed as graphically in Figure 11.

Figure 11 shows that the designed whole control system framework is actually an extension of traditional control system and still composed of three parts that are elaborated as follows.

- *Part 1:* a generalized controller. Human dispatchers, who are regarded as executors of social factors, are integrated with comprehensive effects of the WoC to constitute a generalized controller facing to the human and society.

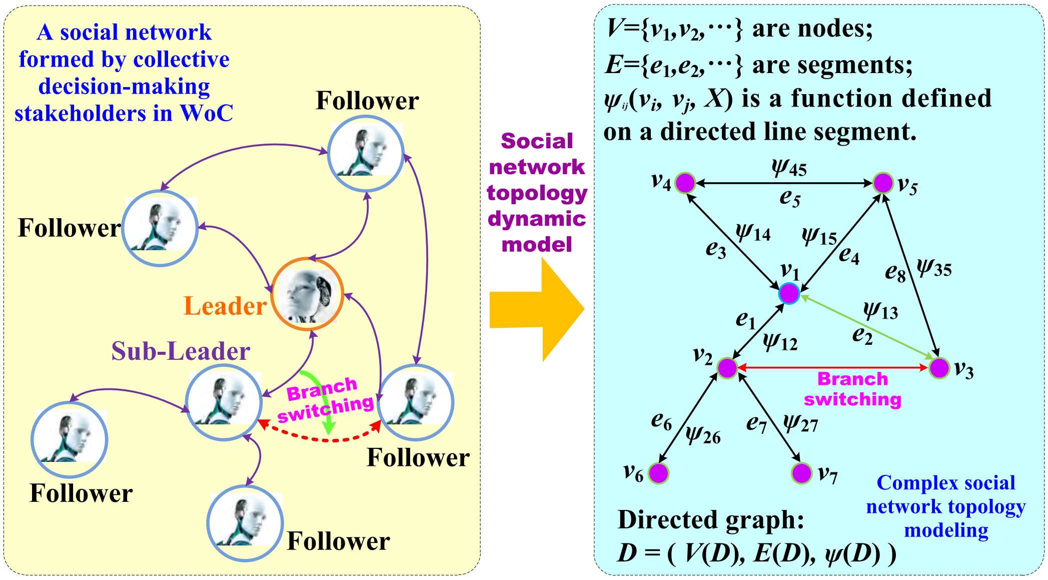


FIGURE 10. The social network formed by the group decision-making agents in WoC and the topology switching relationship between them.

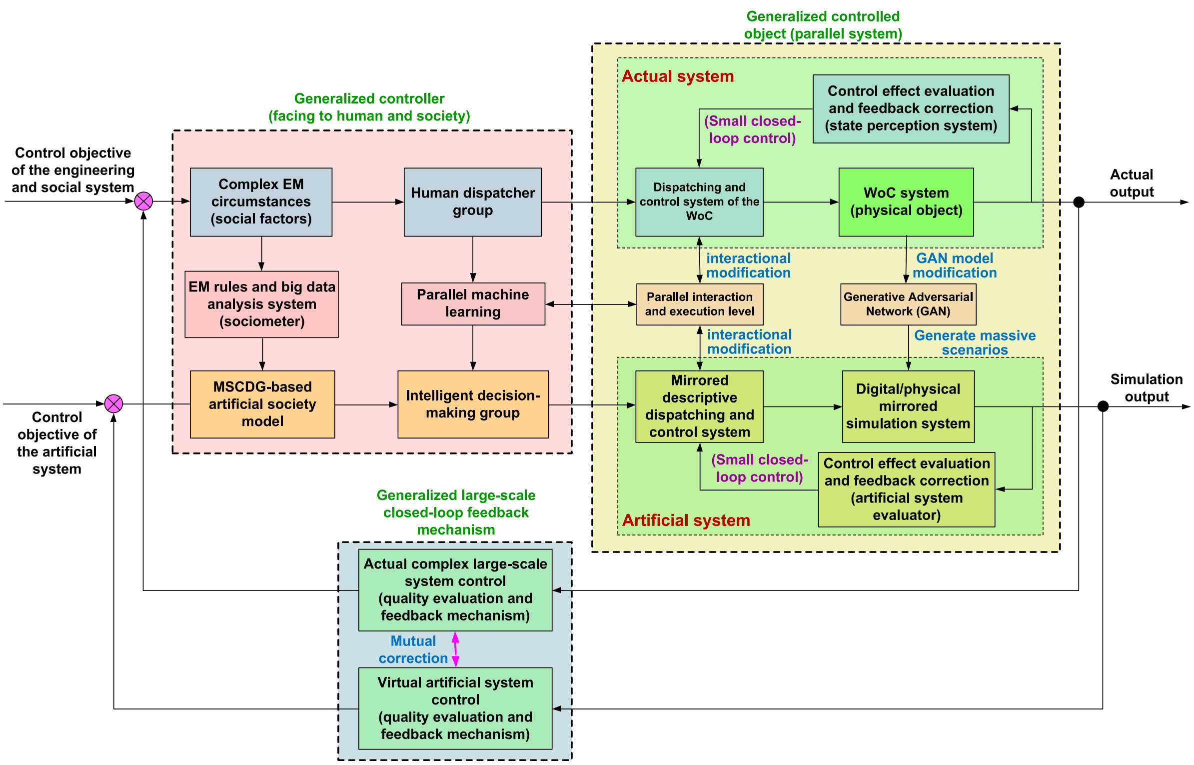


FIGURE 11. Design of the closed-loop framework of the parallel simulation system for the WoC integrating CPSS.

- *Part 2:* a generalized controlled object (i.e., the parallel system). The closed-loop control system of the physical WoC system is combined with a parallel artificial system to form a generalized controlled object. Therefore, the generalized controlled object contains an actual system and a corresponding artificial system, and they constitute a parallel system.
- *Part 3:* a generalized large-scale closed-loop feedback manager. The generalized large-scale closed-loop feedback is employed to evaluate the outputs of the entire

parallel system, involving the causal changes in human and social attributes due to output control.

Based on the three parts above, in order to achieve the self-organization criticality phenomenon and emergence phenomenon generated in the complex system, it is essential to establish a mechanism that can produce complex dynamic states. For this purpose, this paper proposes to build a GAN [54], [97]–[99] to generate massive scenarios for the digital/physical mirrored simulation system, as illustrated in Figure 11. In this figure, this simulation system is capable of automatically generating a large number of scenarios based on GAN and its Monte Carlo simulation method. Moreover, the statistical analysis methods are further applied to observe the self-organization criticality phenomenon and emergence phenomenon, which may occur in the self-organization behaviors of the WoC, so as to lay a firm foundation for the emergence of group knowledge and group intelligence.

C. COMPREHENSIVE MODELING THEORY USED FOR THE CPSS-BASED SELF-ORGANIZATION COUPLING NETWORK OF WOC

There is a class of stability analysis methods based on dynamics mathematical models, such as the transient energy function method [100] and the small signal stability method [101], that are very appropriate for studying the MSCDG-based network dynamics models proposed in this paper. Moreover, a more complete stability analysis theory has been built up in the MSCDG model based complex network theory system. Such stability analysis theory will be discussed in detail in next section.

Among these above-mentioned stability analysis methods, simulation methods are most effective currently in complex systems research, especially for the study of self-organization criticality phenomena and emergence phenomena of human and social behavior. Therefore, we suggest combining the analytical methods based on the mathematical model of MSCDG with the simulation methods based on parallel system theory to form a comprehensive modeling method for the stability analysis of self-organization coupling network of the WoC integrating CPSS in the future. This will help to form a novel comprehensive self-organization coupling modeling theory with theoretically rigorous mathematical basis and applicability in engineering for the WoC.

IV. SYSTEM STABILITY ANALYSIS IN THE PROCESS OF NEW KNOWLEDGE EMERGENCE

In this section, we investigate three types of typical stability issues for WoC in the process of new knowledge emergence, as follows:

1) Issue 1: Complex network dynamics of the WoC and evolutionary stability in the process of network topology evolution;
2) Issue 2: Evolutionary game stability of group decision-making of the WoC in the complex circumstances of EM;
3) Issue 3: Operation stability of the WoC in the complex scenarios generated by the GAN.

For the issue 1, which refers to an evolutionary stability issue for the CPSS network nodes and branches of WoC on a long-time scale (e.g., month, quarter, and year), in a dynamic variation process of network structure and inner and external coupling modes. Therefore, the issues of network synchronization and network traction fall into this category, which are also basic issues commonly investigated in the field of complex network theory.

For the issue 2, which, in the complex circumstances of EM, relates to evolutionary stable equilibrium points searching on different time scales in a dynamic evolution process of mutual game relationships between different intelligent decision groups representing various cells or distributed equipment in WoC. Such issue is also called an evolutionary game stability issue in the process of group decision-making in the game theory field.

For the issue 3, which in the sense of classical control theory and Lyapunov stability theory refers to the operation stability of a dynamic system; thus, it involves the transient and static operation stability of such system with various disturbances on different time scales in a complex scenario. The well-known power system stability analysis generally refers to such operational stability. Based on this, the investigations in this section are elaborated as follows.

Therefore, aiming at the three types of issues mentioned above, we design a framework for the dispatching and stability control system of the WoC, which is illustrated in Figure 12. In order to investigate this framework for the WoC, we suggest taking four steps as follows: the first step is to determine the functions and market role of the cells in WoC with different voltage levels from the perspective of power generation, transmission, transformation, distribution, and utilization; the second is to match the dispatching and control functions of different cells with the dispatching and control strategies of different time scales; the third is to match the roles of cells in EM transactions; and the last step is to develop the mathematical models and simulation models for the cyber-physical-social integrated networks based on precious three steps. More details about the four steps are discussed in the following sections.

A. COMPLEX NETWORK DYNAMICS OF THE WOC AND ITS EVOLUTIONARY STABILITY ISSUES IN THE SELF-ORGANIZATION EVOLUTION OF NETWORK TOPOLOGY

In this section, we first investigate specific issues and then general issues, or first study small-scale power grid models, and then large-scale ones. Specifically, first, we can select the IEEE standard examples that we are familiar with as well as the actual grid models that we have been established, including Hainan power grid, Shenzhen power grid, and Jiangsu Yancheng power grid models. Then, according to the idea of weak-centralization of the WoC proposed in this paper,

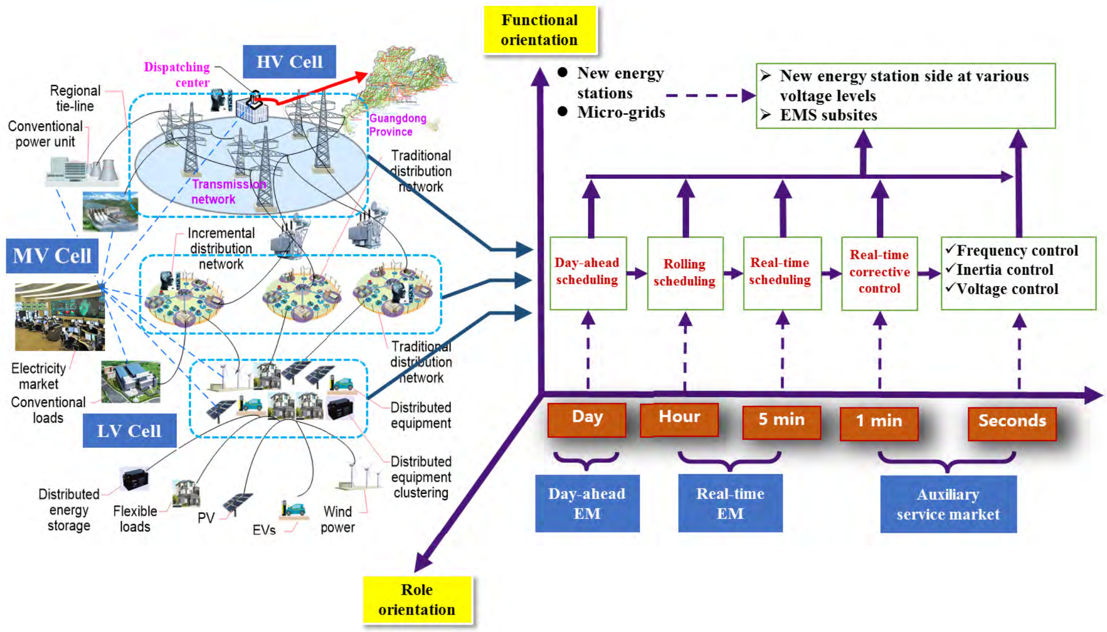


FIGURE 12. A framework designed for the dispatching and stability control system of the WoC based on three types of stability issues discussed in section IV.

we can build a MSCDG-based WoC model for the objective power grid.

We have established the MSCDG-based dynamic mathematical model in previous sections, whose stability is still analyzed based on Lyapunov's First Law and Second Law. However, it is still difficult to directly deal with the non-linear functions in equations (1), (3), and (4), such that we can only perform it in a small-scale and simple network. Therefore, currently, a more sophisticated way to address such issues is to convert the non-linear function into a linear equation via linearization for stability analysis, such that these issues can be transformed into the issues of eigenvalue analysis of a linear network equation. For a continuous MSCDG equation with time delays, we can transform it into a discrete model with control input after linearization and it is demonstrated as

$$\begin{aligned} \boldsymbol{x}_i(k+1) &= \boldsymbol{A}\left(r(k)\right)\cdot x(k) + \boldsymbol{B}\left(r(k)\right)\cdot f\left(x(k)\right) \\ &\quad + \boldsymbol{C}\left(r(k)\right)\cdot g\left(x(k-\tau_1)\right)\cdot \boldsymbol{D}\left(r(k)\right) \\ &\quad \cdot \sum_{v=1}^{\tau_2,\, r(k)} h\left(x(k-v)\right) + \boldsymbol{u}(k) \end{aligned} \tag{6}$$

where $\boldsymbol{A}$, $\boldsymbol{B}$, $\boldsymbol{C}$ and $\boldsymbol{D}$ are the Jacobian matrices of the non-linear function matrix after linearization; $\boldsymbol{f}(k)$ and $\boldsymbol{g}(k)$ are non-linear function vectors; τ_1 and τ_2 are time delays; $\boldsymbol{u}(k)$ is the control input matrix.

Therefore, based on the above linearization processing, we can design a generalized feedback controller, i.e., $\boldsymbol{u}(k) = \boldsymbol{K}\big(r(k)\big)\cdot\hat{\boldsymbol{x}}(k)$, through constructing a Lyapunov-Karsovaskii Functional (LKF) [102]–[105] which can be used to determine whether such networks reach stability and achieve synchronous regulation. Here, $\boldsymbol{K}\big(r(k)\big)$ is the generalized controller gain matrix (feedback coefficient), and $\hat{\boldsymbol{x}}(k)$ is the generalized state vector.

Based on (6), we can analyze the synchronization between different sub-networks coupled to each other as well as their traction method. To this end, we adopt two methods for analysis, including drive-response method and continuous perturbation feedback synchronization method, which are introduced briefly as follows.

a) Drive-response method. In 1991, Badola *et al.* [106] proposed that the MSCDG model can be further divided into two subsystems: the drive-type subsystem and the response-type subsystem (be driven). The former is a stable subsystem with negative Lyapunov exponents and the latter is an unstable subsystem with at least one negative Lyapunov exponent. Therefore, based on the coupling relationship between them, we can use the former as the latter's drive (i.e., the controlled input), so as to draw the latter to reach a synchronous stable state. Kocarev *et al.* [107] and Kocarev and Parlitz [108] improved this drive-response method as active-passive method in 1995, and the principle of which is similar to the drive-response method.

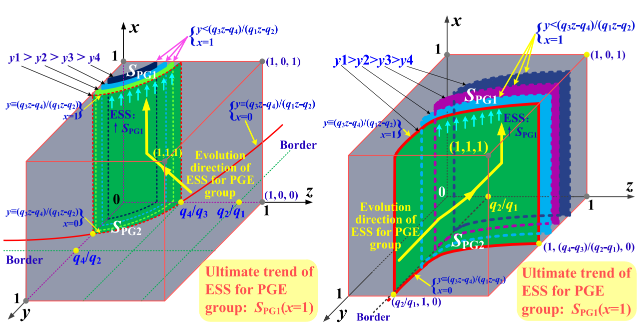
*b) Continuous perturbation feedback synchronization method.*Pyragas [109]–[111] proposed that by continuously fine-adjusting the feedback coefficient $\boldsymbol{K}$ of the controlled input $\boldsymbol{u}(k)$, the synchronization of the aforementioned two sub-networks can be achieved, thereby realizing the control of continuous variable perturbation feedback for a non-linear continuous system.

As can be seen above, the selection and design of the generalized feedback controller designed in Figure 11 will be very interesting. Although this controller is not just a concept of controller adopted in conventional control theory, it also includes generalized control actions that can be used to perform external interferences (i.e., the tractions). For the characteristics of WoC, it is clear that this direction can be explored with many useful concepts and strategies.

B. STRUCTURE STABILITY ANALYSIS FOR THE SELF-ORGANIZATION EVOLUTION OF THE MSCDG-BASED CPSS NETWORK

EGT was first proposed by Smith and Price [83] in 1973 in study of biological evolution phenomena. Unlike traditional game theory, EGT adopts natural selection mechanisms without a need for strict rationality assumptions, making it closer to actual situations. There are some very important concepts commonly used in EGT, including multi-group evolutionary stable strategy (MESS), replicator dynamics (RD), and asymptotically stable equilibrium point (ASEP). It is still possible to use the method elaborated in the previous section to construct the Lyapunov-Karsovaskii functional for discussing the evolutionary stability issues of group games. The authors have carried out some tentative investigations in this field, where we have studied the convergence of the multi-agent asymmetric evolutionary games in an open and ever-growing EM [95]. In particular, we analyzed the strategic convergence characteristics of multiple typical scenarios in the demand-side and generation-side EMs. Figure 13 demonstrates the issues of evolutionary equilibrium stability and dynamic trend of evolutionary stable strategy (ESS) of the PGE group when they participate in time-of-use electricity pricing and electricity sales trading as the typical scenario of the demand-side EM.

In Figure 13, the green surface is a set of ESS of the PGE group, and the other colored surfaces are the set of strategies in the convergence process of the phase trajectory. Figure 13a and 13b represent different game situations that are determined by the distribution parameters q_i in the payment matrix and the probabilities of strategy selection by the individuals in the PGE group, i.e., x, y, and z. Among them, the distribution parameters in the payment matrix include q_1, q_2, q_3 and q_4; x, y, and z are the probability that the PGE group, the NPSE group, and the electricity consumer group execute the pure



(a) Game situation one (b) Game situation two

FIGURE 13. Dynamic adjustment trend of strategy evolution and phase trajectory process of ESS for the PGE group in two typical game situations of the open EM, where (a) shows the ultimate trend of ESS for PGE group is strategy S_{PG1} ($x = 1$) in one kind of game situation, and (b) shows the shows the ultimate trend of ESS for PGE is strategy S_{PG1} ($x = 1$) in another kind of game situation.

strategies S_{PG1}, S_{NP1}, and S_{EC1}, respectively. The solid yellow arrows in the Figure 13a indicate a certain game situation and under which the phase trajectory of the PGE group is finally converged to the pure strategy S_{PG1} after a long-term evolution and development. This strategy S_{PG1} indicates that the PGE group chooses to cooperate with the NPSE group via providing a time-of-use electricity price P_1 that allows the NPSE group to achieve more benefits. Figure 13b demonstrates another game situation and under which the PGE group finally evolve to the same stable pure strategy S_{PG1} with execution probability of x.

Figure 13 also depicts that after a long-term evolution and development of the PGE group, the ultimate ESS developed in this group can resist any mutation strategy produced by other variation individuals to invade the group. Hence, all individuals in this group constantly imitate, train and learn from each other, so that the system will eventually achieve a dynamic equilibrium, called evolutionary stable equilibrium. In this equilibrium stable state, any individual will not be willing to change its strategy unilaterally, thus this equilibrium must be evolutionary/Nash equilibrium (actually it is a refined Nash equilibrium), and in which the PGE group can eventually achieve an evolutionary stable state.

When the number of agent or group involved in the multi-group evolutionary game is more, these evolutionary stability states produced by the evolutionary games in the group will be very complicated. To address it, traditional analytical methods are usually employed to convert the multi-agent stakeholders into solving of multiple two-two gaming issues. However, this is almost impossible to obtain the ideal Nash equilibrium solutions. Hence, traditional analytical methods have been difficult to solve such complex problems. This requires us to combine the simulative methods in more in-depth and systematic investigation work in the future.

C. OPERATING STABILITY ANALYSIS OF THE CPSS BASED ON GAN AND PML

The investigation on the occurrence of various self-organization critical phenomena and emergent phenomena in the complex systems described in this paper must be relied on massive simulations and statistical analysis. Therefore, with the help of parallel system and GAN, we propose to use the GAN generated in Section III from WoC self-organization evolutionary behavior to construct a complex and diverse dynamic game circumstance for WoC, as illustrated in Figure 11. This idea can facilitate investigations of intelligent methods which are used to motivate the emergence of new group knowledge/intelligence and new phenomena in the complex systems, as well as self-organization evolution rules of WoC in a complex and random environment, such that contributing to the in-depth investigation of the guidance and stabilization effects of general pure strategy and mixed strategy in the stability of self-organization evolvement of WoC in complex circumstances.

Therefore, in this section, we need to introduce mathematical statistics and analysis models as a mathematical tool

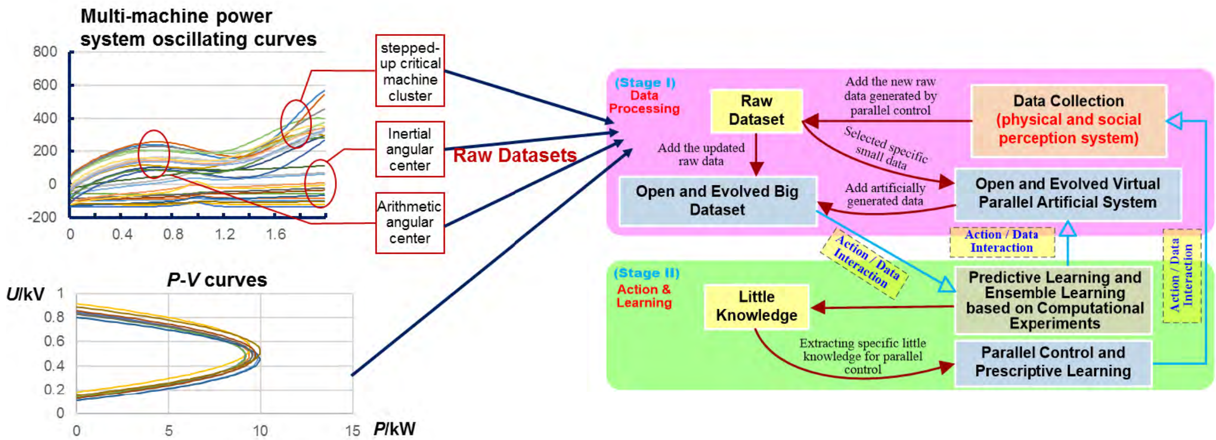


FIGURE 14. Theoretical framework of massive scenarios and data generation based on the principle of parallel system.

to extend the conception in Figure 11 to the new ideas of big data analysis [54], which is illustrated as graphically in Figure 14, where we employ the GAN and parallel system to construct massive scenarios for mathematical analysis via two implementation stages as follows.

Stage I (A Stage of Data Processing): In this stage, first, we use the parallel learning method to select specific small data from actual physical raw data (e.g., the data of operational modes, system parameters, typical events, and dispatch and control system parameters) and artificial society model; second, we input these small data into the virtual artificial system to generate a large amount of new data; lastly, we use these artificial data together with the specific raw small data to constitute the big data sets which will be learned for the issues we need to investigate and address. These big datasets after being learned can be used for updating the ML model.

Stage I (A Stage of action and Learning): In this stage, we still follow the thought of MDP during the process of parallel learning. In other words, we use state transfer function to characterize the dynamic changes of the system during the process of learning from the synthetic big data, such that the knowledge that has been learned will be finally stored in the system state transfer function.

According to the role of the two stages elaborated above, we may need to add another stage, called Stage III, into a complete process of parallel learning. This is because the WoC proposed in this paper will be an open system, in which the artificial system we have constructed will also need to be open inevitably. Moreover, the change of raw data set and artificial system will also lead to a variation in the original data set. Therefore, we must add another stage into the theoretical framework of original two-stage parallel learning described in Figure 14. The Stage III is described as follows.

Stage III (A Stage of Enhancement for interactions between Data and Actions): In this stage, data and actions are continuously kept reactivity and enhancement, which, in essence, can be regarded as a process of retaining and eliminating the big datasets.

As demonstrated in Figure 14, we can adopt predictive learning and ensemble learning to extend classical ML methods from the perspective of dispatching robot, as follows:

- Simultaneous learning of multiple robotic dispatchers. Each of them as an agent who can independently obtain a series of observation data and take a series of actions to form a set, respectively.
- For each robotic dispatcher, its obtained data and number and time of actions taken are independent. Moreover, in the process of PML, actions are allowed to generate multiple new data. Besides, data acquisition and actions taking are performed in a very different frequency and order of occurrence.
- A perspective of parallel world is adopted to observe the evolution of system states, i.e., the newly acquired data is mapped into parallel space, and then the results of anticipatory actions are predicted and analyzed via mass and long-term simulation iterations, and the optimal action is eventually returned back to the real space.

Based on the above extensions, the coupling between data and action can be decreased and the existing reinforcement learning methods will be greatly extended, which can be seen as a result of employing individual robotic dispatcher to conduct medium and long-term simulation iterations for predicting and analyzing the anticipatory actions. In addition, the generations of data and action are relatively independent without time alignment. Hence, this is a typical realization process from actual small data to virtual big data. In fact, the above three extensions have been fully embodied in AlphaGo [57]–[59]. Based on the framework of PML presented in Figure 14, the independent ML ability of individual robotic dispatcher in a centralized dispatching manner can be greatly improved. Figure 15, the principle of PML for individual robotic dispatcher can also be visually explained by the Data/Action diagram of AlphaGo.

Figure 15 shows that the parallel world can be viewed as an integration of data sets and action sets, and while,

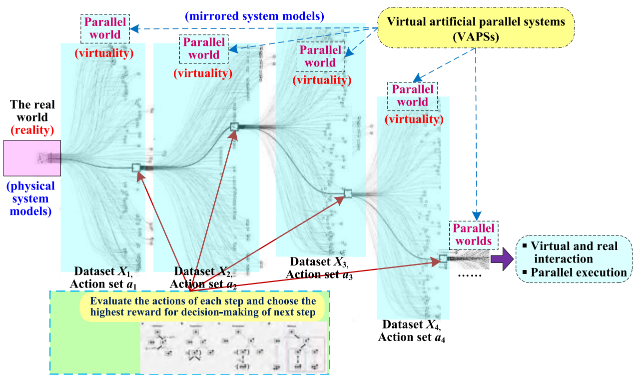


FIGURE 15. Principle explanation of PML of individual robotic dispatcher based on AlphaGo that is demonstrated in [57]–[59].

multiple virtual parallel worlds are generated via the virtual artificial parallel system (VAPS). In the parallel learning system of robotic dispatcher, the data in the real world can be mapped to the parallel world (i.e., the real existing operation states) which is generated by the VAPS, and then a multi-line iteration approach can be adopted to calculate various possibilities that the real world evolves into other parallel worlds, mathematically, i.e., the possibilities that the current state transfers to other states. In this process, the decision-making of each step is evaluated by reinforcement learning algorithms (e.g., ADP, Q-learning), such that the action with highest reward is chosen for decision (i.e., a MDP). In addition, the ensemble learning in Figure 14 is suitable for ML of group robotic dispatchers, which contains mechanisms of multi-agent dispersed learning and collaborative learning.

As stated previously in [54] and [64], Wang proposed a detailed basic framework of parallel learning and the concept of ACP (i.e., artificial society, computational experiments, and parallel execution). On this basis, and according to Figure 11, Figure 14 and Figure 15, we can design a parallel control execution framework for the interactions between virtual worlds and real words based on the robotic or human dispatchers, as illustrated in Figure 16.

D. DISPATCHING AND STABILITY CONTROL SYSTEM FRAMEWORK INVESTIGATION FOR WOC

The stability analysis in this section will lay a solid foundation for design of the overall framework of the dispatching and stability control system of the WoC. In a traditional power system with a centralized control mode, its stability control framework in general is a hierarchical and radial control system architecture which is centered on the dispatching departments at all levels. However, the WoC in this paper possesses a new type of weakly-centralized dispatching and control system which is highly independent and relied on limited boundary information. Table 2 demonstrates a kind of control architecture for the dispatch and control system of WoC. This architecture is originally proposed and recommended by ELECTRA for the WoC [18]–[20]. In Table 2, the system control architecture of the WoC still follows the traditional hierarchical control mode. However, since each cell in WoC needs to communicate and coordinate with the neighboring cell/cells, resulting in the specific content of each level will change accordingly. As depicted in Table 2, apart from primary voltage control (PVC) and pose-primary voltage control (PPVC), ELECTRA also puts forward four levels, including Level 1—inertia frequency control (IFC), Level 2—frequency containment control (FCC), Level 3—balance restoration control (BRC), and Level 4—balance steering control (BSC). Next, the voltage and frequency control of the WoC system proposed by ELECTRA are briefly introduced according to [18]–[20] as follows.

TABLE 2. The control structure of voltage control and frequency control of the WOC system.

Number	Function	Level	Voltage/frequency control mode
1	Voltage control	/	PVC
2			PPVC
3	Frequency control	Level 1	IFC
4		Level 2	FCC
5		Level 3	BRC
6		Level 4	BSC

1) VOLTAGE CONTROL

The voltage control overall structure in WoC [18]–[20] is illustrated in Figure 17. Compared with traditional primary voltage control structure, the voltage control mode (i.e., the primary voltage control) of WoC presented in Figure 17 has not been changed substantially, except the fact that the resources used for voltage control in the PVC of this system have been changed from traditional large-scale generating units to a large number of distributed energy and renewable energy sources.

In addition, the action time of PVC is very short and it is generally millisecond grade, thus we can realize automatic regulation through automatic voltage control (AVC). The function of PVC is completed inside the cell of the WoC, and the resources used for voltage control by the PVC include the power generation units, loads and energy storage equipment in the cell, as well as the flexible AC transmission system (FACTS) equipment. The purpose of PPVC is to eliminate the voltage deviation so as to make the voltage equal to the rated value. At the same time, the network loss is reduced via reactive power optimization. In terms of function, the PPVC is designed to implement optimization of system security and economy of internal areas of the cell, thus the functions of traditional secondary voltage control and three-time voltage control have been integrated in PPVC

2) FREQUENCY CONTROL

The frequency control overall structure in WoC [18]–[20] is illustrated in Figure 18. Compared with traditional three-time

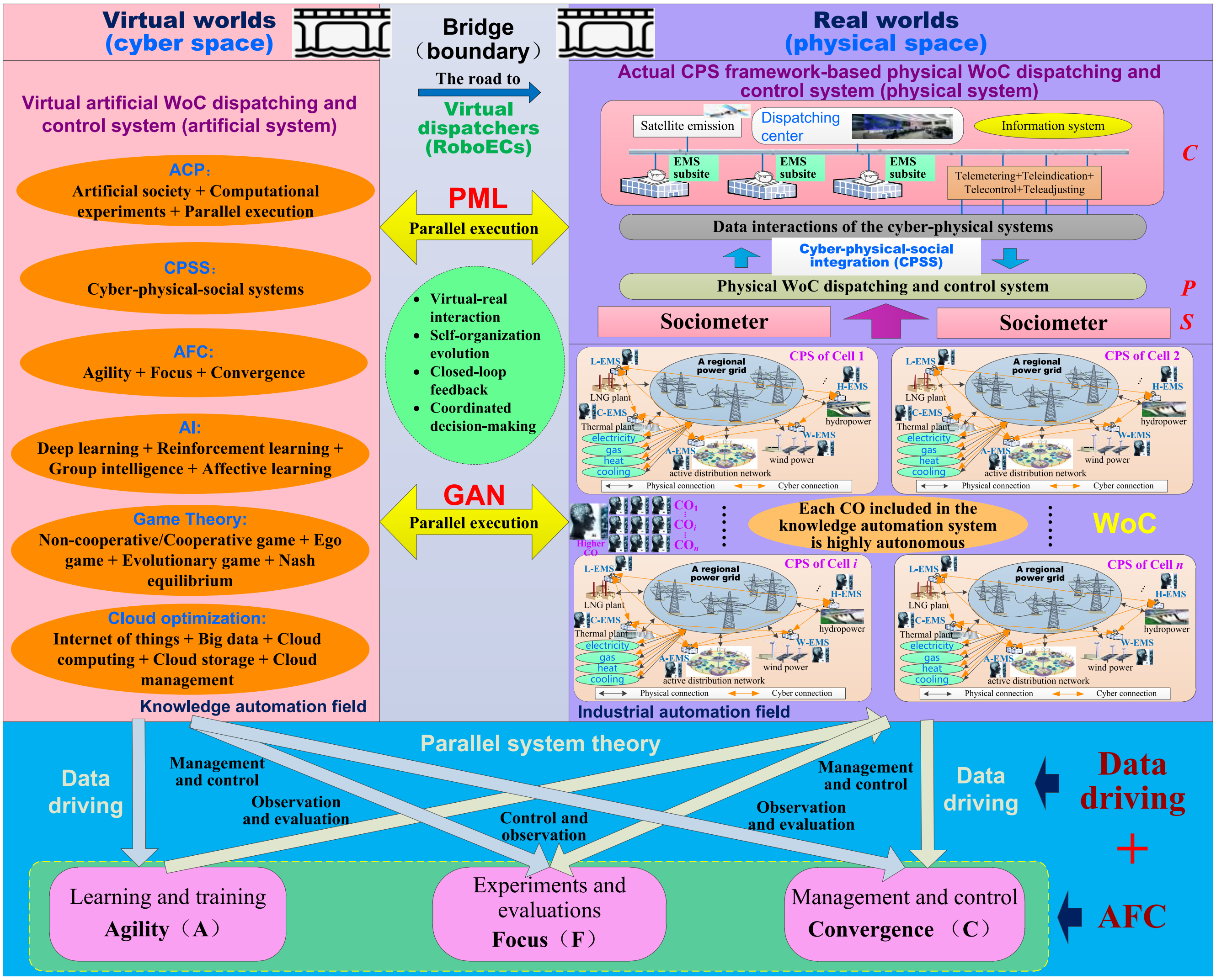


FIGURE 16. A parallel control execution framework for the WoC based on interactions between virtual worlds and real worlds by collective robotic or human dispatchers.

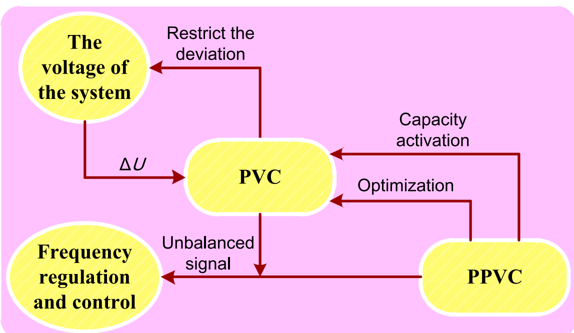


FIGURE 17. The overall framework of voltage control designed in WoC that is proposed by the ELECTRA.

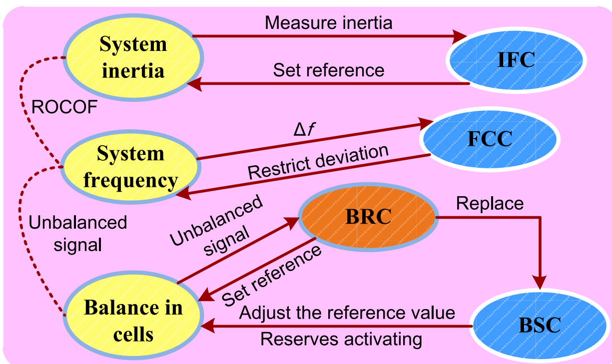


FIGURE 18. The overall framework of frequency control designed in WoC that is proposed by the ELECTRA.

frequency control, the function of IFC has been added into the WoC system, which is equivalent to reestablishment of a relationship between the rotational speed of electric generator and the grid frequency, so that the hidden inertia of the system can be released via the control of power electronics at the first time once the frequency is unstable. As shown in Table 2, the four levels of frequency control are briefly introduced as follows.

Level 1: this level is IFC, and its purpose is to make the rate of change of frequency (ROCOF) of the system not exceeds the maximum allowed. The CO monitors the inertia reserve of power generating units or loads. Thereby, according to the frequency deviation and ROCOF of the system, an activation scheme for the inertia reserve capacity can be determined. Then, this activation scheme is implemented by the IFC in order to realize the regulation of the ROCOF of the system. At this point, the IFC is usually employed to coordinate with the FCC so as to improve the transient stability of the whole system.

Level 2: this level is FCC, and its goal is consistent with the goal of conventional primary frequency control, i.e., utilize the inherent load frequency characteristics of the system and the speed controller effect of generating unit to effectively avoid the system frequency deviations from exceeding the allowable range, such that FCC is capable of rapidly regulate the system frequency deviation to the greatest extent. The major difference between FCC and traditional primary frequency regulation is that the capacity used for frequency regulation via FCC has been changed from traditional generating unit to DG cell and renewable energy source. However, due to the intermittency, randomness, and volatility characteristics of renewable energy source, the frequency fluctuation will occur frequently, thus the requirements of rapidity and sensitivity for the FCC are also higher.

Level 3: this level is BRC. Its goal is similar to traditional secondary frequency regulation, i.e., the internal power balance of the cell is recovered via regulating the power flow in the cell. Normally, the traditional secondary frequency regulation is implemented for the provincial large-scale power grids, and the performance indexes are the index system of control performance standard. However, the BRC not only completes the secondary adjustment of the system frequency, but also needs to regulate the power flow in the cells so as to restore its internal power balance and the power exchange error of the connection line between the cells in WoC. The regulation of BRC is implemented in the cells, which is considered as the core of autonomy for the cells. At this point, the resources used for balance control are originated from the generating units, loads and energy storage units in the cell. In addition, the implementation of BRC is only based on local information and completed inside the cell. In order to achieve global optimization of the system, we need the next level (i.e., the Level 4) to complete this goal.

Level 4: this level is BSC. It is an important link to achieve mutual coordination and cooperation between adjacent cells in WoC. The first goal of BSC is to prevent potential accidents through short-term predictions, and the second is to replace the BRC decision with BSC decision so as to achieve economic optimization.

Obviously, from the perspective of complex network theory and smart dispatching, there are still many aspects that are worth discussing and improving for the control structure presented in Table 2. For example, Table 2 does not include contents regarding how to conduct network traction and game strategy guidance.

Based on the stability analysis of complex systems, we deem that the control architecture of WoC proposed by the ELECTRA should be further integrated with the investigations in this paper. In addition, we should draw on the security and stability control structure of the three lines of defense in the traditional power systems, thus we can effectively investigate the coordination framework involving transient stability control, static stability control, and dynamic stability control, and finally form a new system architecture that is truly feasible in engineering for the optimal dispatching and stability control of WoC. This will also lay a firm foundation for the investigation of the CID level of WoC in next Section V and Section VI.

V. CELL AUTONOMY IN WOC BASED ON INDEPENDENT INTELLIGENT DECISION-MAKING ABILITY

In this section, we will investigate the intelligent decision theory and method for the autonomy of highly independent cells in WoC. The cell here is an independent unit in WoC. There is a considerable difference between the cells with different levels of voltage, which reflects that the compositions of power source, network, load and stored energy within the cell are quite different, and the participation degrees of them in dispatching and control of the power grid are pretty different as well. Therefore, based on this, we conduct investigations on the independent cells across two dimensions, i.e., one is the dimension of voltage level, and the other is the dimension of system state. In the former dimension, we need to carry out investigations on CID theory for different types of independent cells in WoC, such as the high-voltage level of cell (i.e., transmission network with a HV CO), medium-voltage level of cell (i.e., transmission/distribution network with a MV CO), and low-voltage level of cell (i.e., distribution network with a LV CO). In the latter dimension, we should focus on the independent decision-making level of a highly autonomous cell in WoC. The major issues are the coordination of voltage, frequency and inertia between the autonomous cells. Based on the two dimensions above, specific research contents of this section are elaborated as follows.

A. FREQUENCY AUTONOMY

We have conducted in-depth investigations on CID theory for the frequency control and automatic generation control (AGC) system. However, these previous investigations are generally based on conventional power supply structures, which are mainly composed of hydro-power generating units and thermal generating units. During the investigation, although we have considered the participation of DGs and EVs in frequency control of power network, we did not conduct this investigation in accordance with the structure of DG with high degree of penetration, nor did we considered the system inertia, as well as the influence of social behavior factors of various agents participating in frequency regulation in the cell. Based on previous research work, we can continue to conduct further investigations in this direction elaborated above as follows.

First, for the high-voltage level of cells, their frequency control strategies can still follow the traditional control strategies. It is well known that the power grids with high-voltage levels are generally transmission grids, while traditional large-scale generating units such as hydropower, thermal power, nuclear power, gas- and pumped-storage are directly connected to the power grids with 220/500kV voltage level. The primary frequency regulation and AGC on which traditional frequency control relies are both implemented with these large-scale generating units. For high-voltage cells, there is generally no self-organization coupling phenomenon occurred in these cells, due to that the connections of large-scale power plants to the grid are strictly in accordance with the approval. Therefore, such high-voltage level of cell is still considered as a simple system.

For medium-voltage and low-voltage levels of cells, where a large number of renewable power sources, energy storage equipment and loads will participate in power network frequency control; moreover, in this process, random self-organization coupling phenomenon may occur; thus we should focus on frequency autonomy of such types of cells.

According to the structures of power source, network, load and energy storage, and based on the method elaborated in Section III, the self-organization coupling network with cyber-physical-social integration can be established for the medium- and low-voltage cells. In recent years, we have carried out fruitful investigation in this direction [74], [95], [112]. Concretely, we have adopted a wolf pack hunting algorithm to achieve intelligent frequency control decision-making in a distribution network [74]. In addition, we have used the lifelong learning (which is a kind of transfer learning technique) method to realize complementary generation control of interconnected power grids with high-penetration renewables and EVs [112].

The following is a brief introduction to a concrete example that explains how to use a complex network model and a CPSS-based parallel learning architecture to design an independent intelligent decision supporting system for the autonomous cell in WoC.

In this example, we have adopted complex network theory to conduct CPSS-based modeling of a micro-grid. Addressed concretely, we adopt PML method to implement the collective intelligent dispatching decision-making during the process of third-time frequency regulation of the system. The architecture of CPSS integration in this example is illustrated in Figure 19.

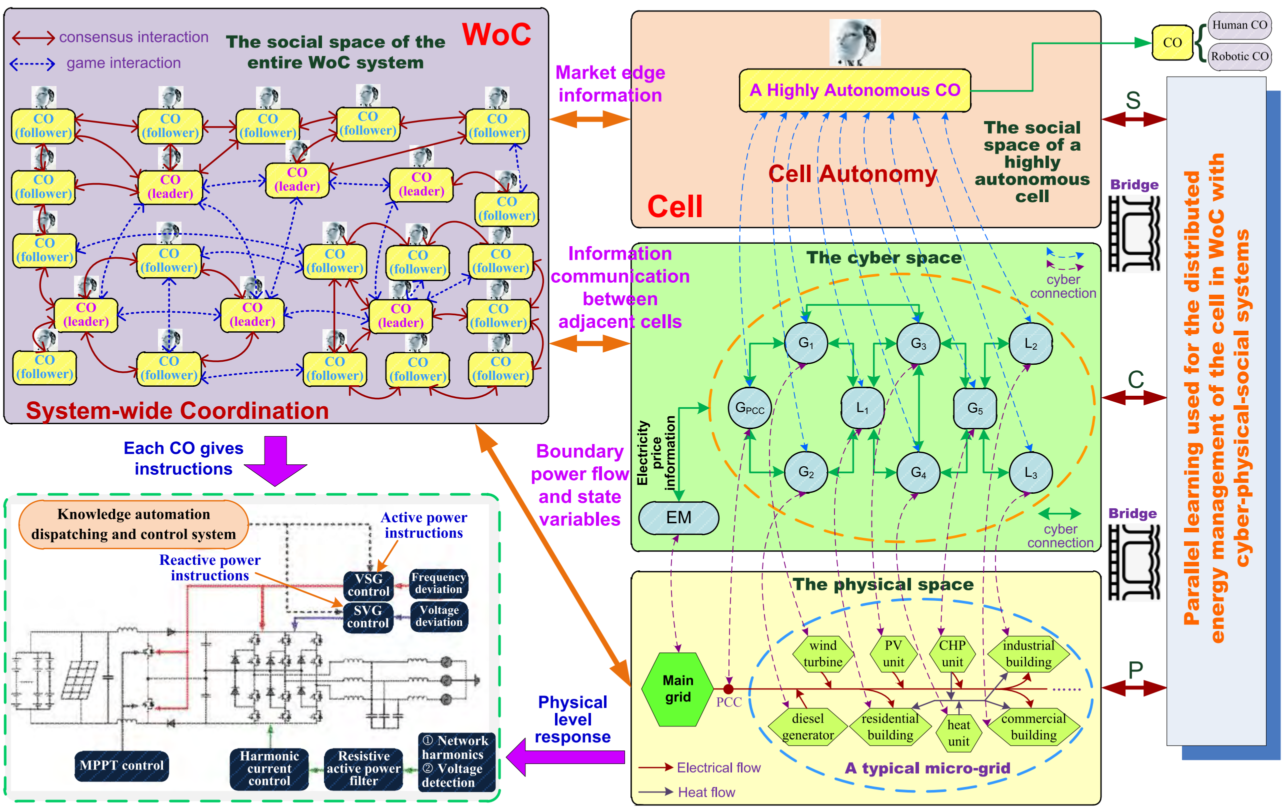


FIGURE 19. A CPSS integration framework designed for the distributed energy management of a highly autonomous cell in WoC (which is a typical micro-grid), where important information such as market edge information from the social space, information obtained from a communication between adjacent cells in the cyber space, and information of boundary power flow and state variables from the physical space will be exchanged with the social space of the entire WoC system to achieve cell autonomy and system coordination. Moreover, the physical level involving VSG control, SVG control, harmonic current control, and MPPT control responds to the above-mentioned information.

Figure 19 shows that the distributed energy management (DEM) system is the energy center of a typical micro-grid, and the designed social system adopts a complex social network model in the social space, which is established based on consensus collaboration strategy and correlated equilibrium (CE) game strategy. In addition, it can be seen that the cyber space (C) is a bridge or link between the social space (S) and physical space (P). The autonomous cell in WoC achieves independent intelligent decision-making based on some edge/inter-neighbor information from other cells, including market edge information, interactions between adjacent cells, and boundary power flow and state variables.

In addition, the CE presented in Figure 19 is reflected in a general-sum game model in the game theory, in which a CE is more general than a Nash equilibrium as the set of Nash equilibria is completely included in the set of correlated equilibria [113]. Obviously, a CE can also be regarded as a Nash equilibrium under a special condition. Generally speaking, a CE is a probability distribution of joint actions from which no agent or no cell is motivated to deviate unilaterally, which can be combined with Q-learning, as follows:

$$\begin{cases} \sum\limits_{\vec{a}_{-l}\in \boldsymbol{A}_{-l}(s_k)} \boldsymbol{\pi}_l\,(s_k,\vec{a})\,\boldsymbol{Q}_l^k\,(s_k,(\vec{a}_{-l},a_l)) \\ \quad \geq \sum\limits_{\vec{a}_{-l}\in \boldsymbol{A}_{-l}(s_k)} \boldsymbol{\pi}_l\,(s_k,\vec{a})\,\boldsymbol{Q}_l^k\left(s_k,(\vec{a}_{-l},a_l^{\mathrm{o}})\right) \\ \boldsymbol{A}_{-l} = \prod_{p\neq l}\boldsymbol{A}_p, \quad \vec{a}_{-l} = \prod_{p\neq l} a_p, \\ \quad \vec{a} = (\vec{a}_{-l},a_l)\,, \quad a_l^{\mathrm{o}} \neq a_l \end{cases} \tag{7}$$

where π_l is the probability distribution of state-action of the lth decision agent, which can be called a CE only when it satisfies the inequality constraint in (7); $\boldsymbol{Q}_l^k$ is the knowledge matrix of the lth decision agent at the kth iteration, which represents the knowledge values of state-action pairs; s_k is the state of the multi-agent system at the kth iteration; $\vec{a} = [a_1,\ldots,a_l,\ldots,a_L]$ is the joint action of all the decision agents; a_l is the action of the lth decision agent; L is the number of the agents; $\vec{a}_{-l}$ is the joint action of all the decision agents except the lth decision agent; $\boldsymbol{A}(s_k)$ is the agents' set of available joint actions in state s_k; $\boldsymbol{A}_l$ is the lth decision agent's set of pure actions; and a_l^{o} is the lth decision agent's any other action except the action a_l.

Based on (7), we can adopt a novel group reinforcement learning method, called CE-Q learning to complete the seeking process of CE presented in (7). This is a knowledge learning process, during which each cell, according to the state-action-reward-state data via continuous interactions with the environment, can update its own knowledge of different state-action pairs with the feedback rewards by reinforcement learning. In this paper, we propose to use Q-learning [114] to achieve this learning process, such that we can store the group knowledge via the Q-value matrix, as follows [115]:

$$V_l(s_{k+1}) = \sum\nolimits_{\vec{a}\in \boldsymbol{A}(s_{k+1})} \boldsymbol{\pi}_l(s_{k+1},\vec{a})\boldsymbol{Q}_l^k(s_{k+1},\vec{a}) \tag{8}$$

$$\begin{aligned}\boldsymbol{Q}_l^{k+1}(s_k,\vec{a}) = \boldsymbol{Q}_l^k(s_k,\vec{a}) + \alpha[(1-\gamma)R_l(s_k,\vec{a}) \\ +\gamma V_l(s_{k+1}) - \boldsymbol{Q}_l^k(s_k,\vec{a})]\end{aligned} \tag{9}$$

where $V_l(s_{k+1})$ represents the state value-function of the lth decision agent in state s_{k+1}; α is the knowledge learning factor; γ is the discount factor; $R_l\,(s_k,\vec{a})$ is the feedback reward after implementing a joint decision-making action $\vec{a}$ under state s_k.

Based on above descriptions, we can obtain the statistical results of the third-time frequency control optimization for a typical testing system. The statistical results indicate that the PML system using the CPSS structure can be well employed to complete independent intelligent decision tasks in an autonomous cell. In addition, this learning system not only has a high-speed convergence, but also possesses the capability of online learning, ensuring that the system remains adaptable sufficiently in a complex and ever-changing environment.

B. VOLTAGE AUTONOMY

As stated in Section IV, the voltage autonomy issue for a highly independent cell is relatively simpler than its frequency autonomy. This is because the voltage control is originally conducted based on local balance, thus we just focus on how to achieve a global optimization effect of reactive power based on limited boundary information and decentralized optimization algorithms in terms of complex network changes. For a highly independent cell in WoC (which is similar to a highly autonomous micro-grid), there have been some investigations regarding its network partitioning and subtasks decomposition for addressing complex power system optimization issues. In addition, we also have a good accumulation of decentralized optimization algorithms (see the work introduction in section VIII). Therefore, what need to be investigated in depth are Nash game theory and Pareto multi-objective optimization method for reactive power coordinated control in an open auxiliary service market. Therefore, we can still carry out relevant investigations in the same way as the previous section on frequency autonomy, which is not repeated here.

C. COORDINATED-CONTROL OF VOLTAGE, FREQUENCY, AND INERTIA IN CELL AUTONOMY

The internal of a cell in WoC is a multi-agent complex system consisting of power source, network, load, and energy storage, especially when the DGs with a high penetration are connected by inverters. At this point, the cell must be relied on DGs to implement stability control of frequency, voltage and power angle simultaneously. Therefore, obviously, the frequency of system, the node voltage and the virtual inertia are very difficult to be decoupled.

Regarding the complex issues of general multi-agent games involving multi-objective coordination and control, the Nash game combined with Pareto multi-objective optimization is a commonly used method to solve these multi-agent game issues. Addressed concretely, we first obtain the Pareto frontier of each decision agent. Then, we use the Pareto frontier of each agent as inputs to form a Nash equilibrium function. Lastly, we solve the Nash equilibrium point of this Nash equilibrium function, which can be called a Nash-Pareto solution. This solution is usually unique, ensuring that the results are win-win for the agents. We have used this method to solve an interactive game among diverse multiple household users and a distribution network in [116]. The obtained results show that the minimum target of peak-to-valley difference and network loss of the grid can be achieved. In addition, the user's electricity consumption comfort and economy goals can also be achieved. Therefore, in this section, we can still adopt the complex network theory, game theory and PML to investigate the CID of an autonomous cell in voltage, frequency and inertia coordination. Specific procedures are as follows.

First, we should address the dynamic issues of network branches. The switching action of all the lines, information links and social relationships inside a cell can be considered as dynamic changes of branches in the network. For the established MSCDG network dynamics model, we can combine evolutionary game with the optimization problems. Hence, as described in Section III and Section IV, we can transform the self-organization coupling process of the cyber-physical-social network topology of WoC into an evolutionary game issue, such that the game equilibrium functions such as Nash equilibrium and CE functions can be transformed into a solving problem of Pareto optimization objective function, in which the dynamic behaviors of network topology can be incorporated into the optimization decision.

Second, we should address dynamic issues of network nodes. The DG, energy storage and loads all can be regarded as dynamic changes of the nodes in the network. Hence, we can still combine the Nash game with Pareto multi-objective optimization to solve this dynamic issue. During the process, the controllable equipment of each node is treated as an agent participating in the game, and each agent's own Pareto frontier can be determined separately. At this point, the entire cell is regarded as an agent, then we can obtain another Pareto frontier based on the targets of global frequency, reactive power and inertial of the whole system. Based on this, the issue to be solved in this section will be transformed into a Nash game issue between system agent and multiple distributed equipment agents. In the process of solving this issue, all the Pareto frontiers are considered as inputs of the Nash game optimization function. Finally, we can obtain a Nash-Pareto solution that is satisfied both by the system and the distributed equipment, as demonstrated in Figure 20.

Generally speaking, the optimization issue of complex systems is difficult to be satisfied with non-convex conditions, thus we can use the methods such as NSGA-II [117], SPEA2 [118], and MGSO [119] to search the Pareto frontier.

Third, we should integrate two optimization decision-making issues of network branch dynamics and node dynamics described in above two procedures. Actually, it is necessary to determine whether need to split the topology and the node into two sub-problems to be solved, or form a unified optimization model to solve the problem, which depends on the size of the independent cell to be investigated in WoC.

Lastly, the above process of optimization decisions making and equilibrium solving is used as the dispatching system of the mirrored VAPS (see Figure 21). Then, use the GAN to automatically generate massive scenarios. In these scenarios, through the offline calculation, a PML-based sample data

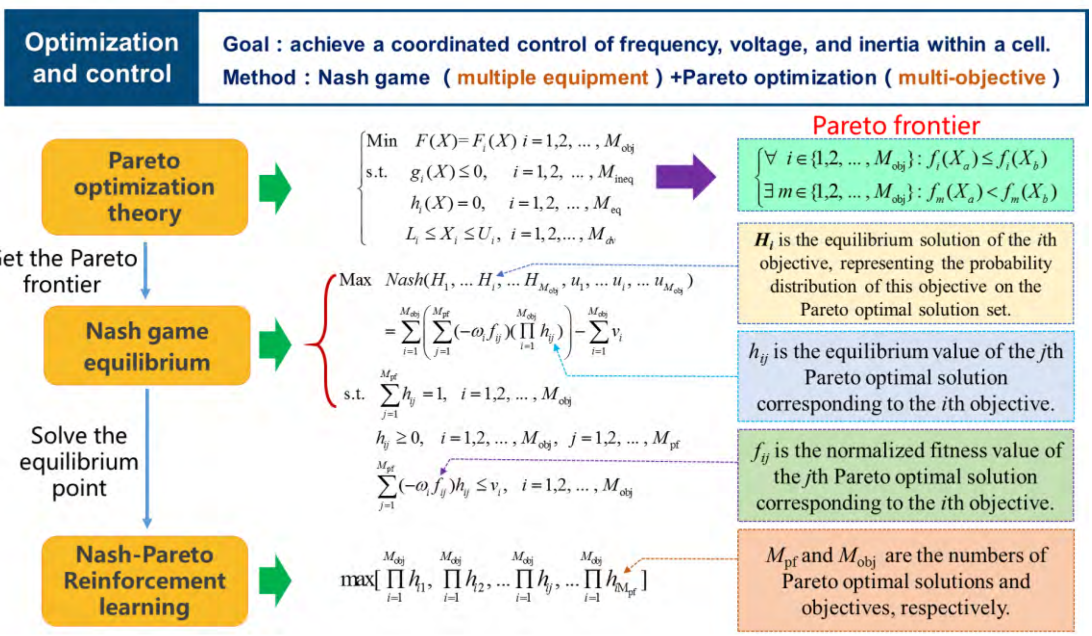


FIGURE 20. Illustration of the proposed Nash equilibrium plus Pareto multi-objective optimization method used for the coordinated control of frequency, voltage, and inertia within a highly independent cell in WoC.

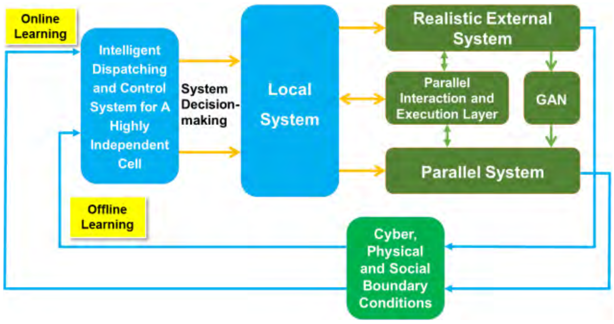


FIGURE 21. A framework constructed based on parallel system and GAN for massive machine learning samples generation.

generating system can be constituted to promote the emergence of collective decision knowledge. Therefore, as shown in Figure 21, we can use parallel system and GAN to construct a large number of physical, cyber, and social boundary conditions to form huge numbers of samples for PML. Through such type of ML, a local optimal dispatching and control strategy is formed under highly random boundary conditions. This is a local optimal dispatching and control strategy obtained based on cyber, physical, and social boundary conditions.

Aiming at the process of dispatching and control decision making in a highly autonomous cell, if the PML system demonstrated in Figure 21 is not considered in this process, the computational complexity will increase exponentially with the changing of network topology structure and the increasing of the number of decision agents and optimization objectives. Furthermore, the time for strategy solving will cannot meet the requirements of voltage/frequency/inertia control in a real-time mode for the autonomous cell. In contrast, although the offline PML is very time-consuming, once the pre-learning is completed, the speed of independent intelligent decision making will be very fast. This is also the biggest advantage of well-known AI systems.

VI. SYSTEM-SIDE COORDINATION OF WOC BASED ON COLLECTIVE INTELLIGENT DECISION-MAKING ABILITY

In this section, we conducted investigations from a system-wide perspective, which aim at CID issues under the circumstance that various highly-autonomous cells are widely interconnected in the WoC. In order to coordinate the interests of stakeholders in a game, the cells in WoC are divided into ones at master-slave levels and ones at same levels. Moreover, aiming at these cells with different statuses, we use asymmetric Q-learning algorithms and Nash Q-learning/Pareto-Q learning algorithms to address such complex game relationships. Concretely speaking, the upper and lower voltage levels of cells are in a master-slave status, and the cells of the same voltage level are in an equal status. For the master-slave relationship, we solve its Stackelberg equilibrium by using asymmetric Q-learning algorithms; and for the equal competitive relationship, we solve its Nash equilibrium via adopting Nash-Q learning or Pareto-Q learning algorithms. For this purpose, two key game issues are discussed in this section as follows.

- *Issue 1:* the master-slave game (i.e., Stackelberg game) and CID issue of an interconnected WoC system consisting of multiple cells in different statuses (i.e., cells at master-slave levels).
- *Issue 2:* the Nash game and CID issue of an interconnected WoC system consisting of multiple cells in the same status (i.e., cells at same levels).

Obviously, it is seen from the two issues that there is a global and local correspondence between this section and the previous section. Therefore, the cells in master-slave level and cells of the same level form a two-level game framework, in which the games among master-slave cells Based on the two issues above, specific contents in this section are elaborated as follows.

A. COLLECTIVE INTELLIGENT DECISION-MAKING FOR THE CELLS AT MASTER-SLAVE LEVELS IN WOC

The WoC proposed by ELECTRA is a weakly-centralized advanced form of smart grid. However, the operation characteristics of actual power systems determine that such weak centralization feature is not equal to absolute decentralization, indicating that the dispatching positions of regional grids and each provincial grid are still very important in WoC. Therefore, from a system-wide perspective, although a high degree of autonomy is emphasized in WoC, the cell operators (COs) with different voltage levels and different functional roles still have an asymmetrical relationship, called master-slave game relationship. In this regard, we propose that we can use Stackelberg game equilibrium to depict such master-slave game relationship between upper-layer and lower-layer cells in WoC in this section, as follows:

$$\begin{cases} \left(\bar{\boldsymbol{x}}_{\mathrm{g}}^{*}, \bar{\boldsymbol{x}}^{*}\right) = \arg \max\limits_{\boldsymbol{x}_{\mathrm{g}} \in \boldsymbol{A}_{\text{leader}}} U_{\text{leader}}(\boldsymbol{x}_{\mathrm{g}}, \bar{\boldsymbol{x}}^{*}), & \text{for the leader} \\ \bar{\boldsymbol{x}}_{m}^{*} = \arg \max\limits_{\boldsymbol{x}_{m} \in \boldsymbol{A}_{m}} U_{m}\left(\bar{\boldsymbol{x}}_{\mathrm{g}}^{*}, \boldsymbol{x}_{m}\right), & \text{for the follower } m \end{cases} \tag{10}$$

subject to

$$\bar{\boldsymbol{x}}^{*} = \left(\bar{\boldsymbol{x}}_{1}^{*}, \cdots, \bar{\boldsymbol{x}}_{m}^{*}, \cdots, \bar{\boldsymbol{x}}_{M}^{*}\right) \tag{11}$$

where m represents the mth follower in a Stackelberg game, and $m = 1, 2, \cdots, M$; M is the total number of followers; $\bar{\boldsymbol{x}}_{\mathrm{g}}^{*}$ is the current optimal strategy of the leader; $\bar{\boldsymbol{x}}^{*}$ is the joint optimal strategy of all followers; $\bar{\boldsymbol{x}}_{m}^{*}$ is the current optimal strategy of the mth follower; U_{leader} and U_m are the payoff functions of the leader and the mth follower, respectively; $\boldsymbol{A}_{\text{leader}}$ and $\boldsymbol{A}_m$ are the decision-searching space of the leader and the mth follower, respectively. Based on (10), then we can use the methods of group Q-learning and transfer learning to form a fast Stackelberg equilibrium learning (FSEL) based CID approach. In this approach, the Q-learning expression is presented as follows:

$$\begin{cases} \boldsymbol{Q}_{mt}^{q,k+1}\left(s_{mt}^{qp,k}, a_{mt}^{qp,k}\right) = \boldsymbol{Q}_{mt}^{q,k}\left(s_{mt}^{qp,k}, a_{mt}^{qp,k}\right) + \alpha \cdot \Delta\boldsymbol{Q}_{mt}^{q,k} \\ \Delta\boldsymbol{Q}_{mt}^{q,k} = R_{mt}^{qp}\left(s_{mt}^{qp,k}, s_{mt}^{qp,k+1}, a_{mt}^{qp,k}\right) \\ \quad +\gamma \cdot \max\limits_{a_{mt}^{q} \in \boldsymbol{A}_{mt}^{q}} \boldsymbol{Q}_{mt}^{q,k}\left(s_{mt}^{qp,k+1}, a_{mt}^{q}\right) \\ -\boldsymbol{Q}_{mt}^{q,k}\left(s_{mt}^{qp,k}, a_{mt}^{qp,k}\right) \end{cases} \tag{12}$$

$$a_{mt}^{qp,k} = \begin{cases} \arg \max\limits_{a_{mt}^{q} \in \boldsymbol{A}_{mt}^{q}} \boldsymbol{Q}_{mt}^{qp,k}(s_{mt}^{qp,k}, a_{mt}^{q}), & \text{if } q_0' \le \varepsilon \\ a_{\text{rand}}, & \text{otherwise} \end{cases} \tag{13}$$

where $m = 1, 2, \cdots, M$; $t = 1, 2, \cdots, M_m$, and M_m is the total number of followers who have interaction with follower m; $q = 1, 2, \cdots, Q_{\mathrm{L}}$, and Q_{L} is the total number of real code for transfer learning of follower m; $p = 1, 2, \cdots, P_{\mathrm{S}}$, and P_{S} is the total number of searching of follower m; and the relevant symbols have been defined in (7)~(11). It should be added that the superscripts q, p and k represent the qth real code for transfer learning, the pth searching, and the kth iteration, respectively; R_{mt}^{qp} is an immediate feedback reward, which can generally be transformed from the optimal objective; $\boldsymbol{Q}_{mt}^{q}$ and $\Delta\boldsymbol{Q}_{mt}^{q}$ are the knowledge matrix and its increment, respectively; q_0' is a random value in the unified probability distribution; ε is a parameter of local greedy searching; a_{rand} represents the global random searching action.

This approach expounded above can be extended to solving the issues of master-slave gaming in multiple autonomous cells. We have conducted a preliminary investigation on this in 2017. Among this, we have employed this approach to secondary frequency control of a power grid in an integrated energy system (IES) considering multi-energy integration. Concretely, we have taken the Hainan Power Grid as an example for analysis, in which this grid is divided into five relatively independent cells in WoC. The EMSs of these five cells together with the EMS of the Power Dispatching Control Center of Hainan Power Grid Corporation constitute an analogous Stackelberg master-slave game framework. The simulation result shows that the effect of frequency control and system operating cost after adopting this approach are obviously better than employing current engineering methods.

However, even for a highly autonomous WoC, the control mode of the entire system voltage is still adopted an analogous system coordination and cooperation between the AVC of provincial dispatching and prefecture-level dispatching. Moreover, the frequency control of the whole system is also adopted a similar cooperation and cooperation relationship between the AGC system of the provincial-level dispatching and the PLC system of the power plant. In addition, the virtual inertia reserve of the whole system also needs to be assigned to the virtual synchronous generating control system of each cell system in WoC. Therefore, we still dynamically allocate the entire goal of the whole system to each cell as a sub-goal through optimization modes, so as to establish an analogous Stackelberg master-slave game framework. Thereby, we can again employ the group reinforcement learning to achieve CID of the entire WoC system. Certainly, although we have determined a basic investigation idea for this part, the amount of specific tasks is still huge, which requires in-depth and meticulous work in the future.

B. COLLECTIVE INTELLIGENT DECISION-MAKING FOR THE CELLS OF THE SAME LEVEL IN WOC

In the context of a completely open EM, the principle of justice is more emphasized. Analogously, various COs in WoC pursue to participate in the market competition or cooperation on an equal footing. However, in the complex circumstances, the games between cells are a kind of hybrid gaming process, which are not simple zero-sum games or cooperative games, but general sum games. The issues of hybrid game in WoC are very complicated, thus it is essential to focus on solving two dynamic issues as follows.

Dynamic Issue 1: it is a dynamic issue that the game relationship will be changed along with the variation of system states under the topology structure of the game among deterministic stakeholders. In particular, at the system-side level, with the change of power grid statuses such as normal, alert, emergence and recovery states, this game process will be experienced with a competitive game, a partial cooperative game and a fully cooperative game. Hence, the preferences of the Pareto solution set corresponding to the three categories of games will also be changed dynamically, such that we need to employ CID algorithms, i.e., Nash-Q, Pareto-Q and CE-Q methods (see Figure 22) to solve the issues of the three types of games, respectively. During the solving process, an intelligent classification for various states can be achieved via using the latest proposed deep forest learning method [120], which can be employed to complete an integration of various ML algorithms.

As demonstrated in Figure 22, a graphical explanation is provided for the dynamic transition between multiple major states and control objectives in the process of active power control in a provincial power grid, where we can extend the deterministic networks to self-organization coupling networks and automatically match the algorithm in this dynamic switching. Moreover, Figure 22 clearly shows that the system state is transferred from a danger zone to an alerting zone, and then to a normal zone, and thereby the preference solutions are also biased towards from correlated equilibria to Stackelberg equilibria, and then to decentralized optimization results.

Dynamic Issue 2: it is a dynamic issue that the number of agents involved in the game together with the social topology structures will also be changed dynamically in an open and ever-growing EM. To address it, we propose to extend the above-mentioned deterministic game network to a self-organization coupling network, and the relevant investigation on which must be conducted by adopting complex network theory and parallel system theory. For this reason, we have carried out some preliminary explanations, among which we have used some basic complex network models such as rule

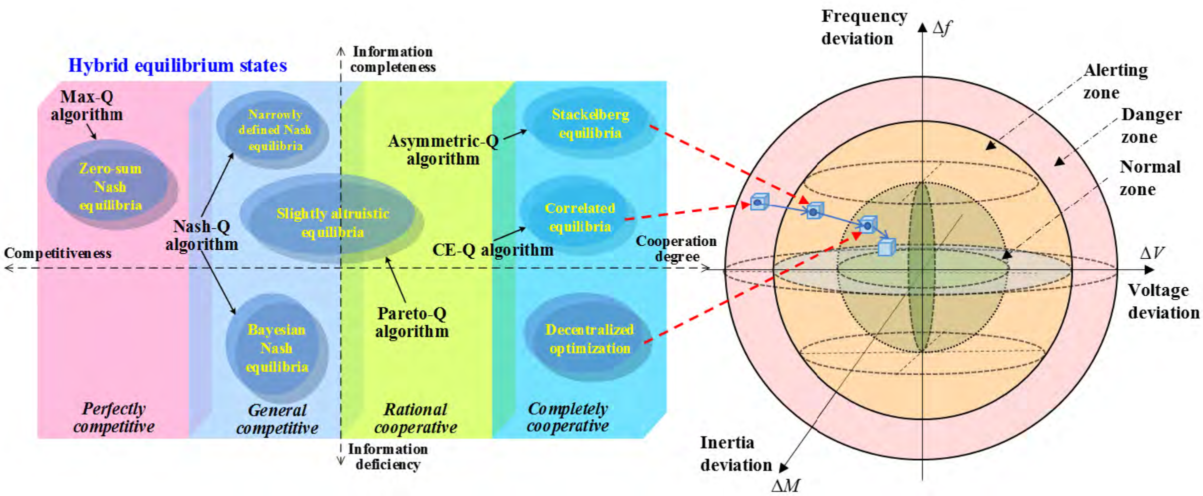


FIGURE 22. Graphical illustration for a dynamic hybrid game among power system active power control and frequency and tie-line power states transfer, where aiming at the dynamic changes in the numbers of cells and social network topology, the corresponding intelligent decision-making methods are developed to deal with these changes.

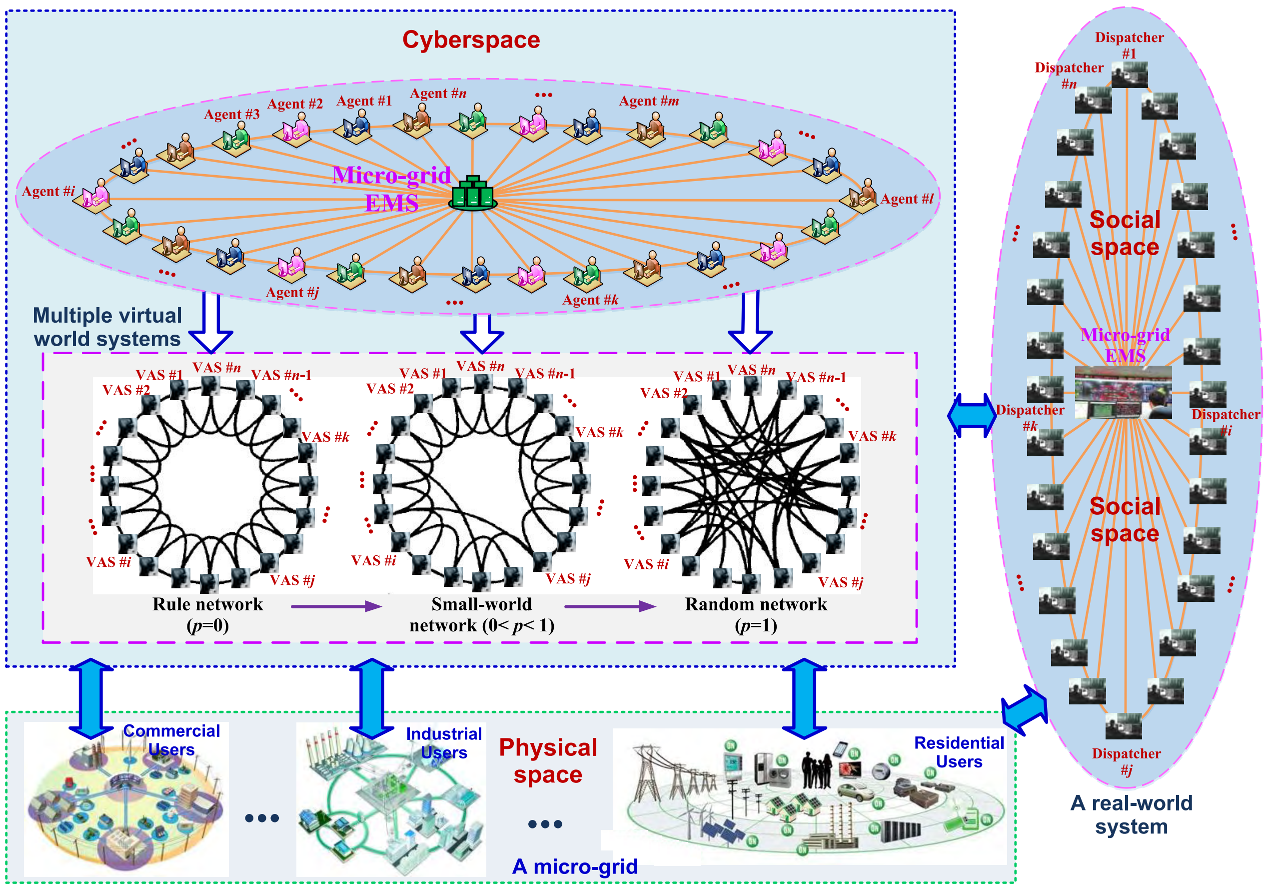


FIGURE 23. The structure of a parallel system for a micro-grid based on the small world network model in complex network theory, which demonstrates the learning with multiple virtual artificial systems (VASs) and a real-world system.

network model (or called lattice graph or d-lattice), random network model, small-world network model [121]–[123], and scale-free network model in complex network theory and parallel system theory [54], [124]–[126] to investigate the smart generation control of a micro-grid. As illustrated in Figure 23, we take the small-world network model as an example. Here, the small world network model is a kind of special complex network model, which is usually regarded as a type of stable network structure formed during a continuous process of self-organizing in complex networks. It is characterized by information interaction adjacent to each other and tending to the minimum communication cost. We have used intelligent algorithms to implement dynamic random adjustments to the interconnection probability of the group with intelligent decision-making abilities. The results are encouraging and indicate that this variable small world network model can successfully avoid the system being trapped into a local optimization. Hence, we believe that a more general self-organization coupling network model can be further used for relevant analysis, and more interesting results will be obtained in the future.

VII. EXPLORATIONS ON SYSTEM DEVELOPMENT AND ENGINEERING PRACTICE OF WOC

In this paper, the theoretical investigation objective is a complete power system consisting of transmission networks and distribution networks. Aiming at engineering practice of this system, we need to put it into practice in some demonstration projects such as the incremental distribution network project and smart distribution network dispatching key science and technology project, such that promoting the application of theoretical results step by step. We believe that some smaller scale of actual power grids may be taken as research targets based on a smart distribution network EMS platform that has been developed previously. For instance, we can consider the Yancheng Power Grid in Jiangsu Province and the Dongguan Power Grid in Guangdong Province as actual investigation objects. Concretely, in the previous stage, we can develop a software platform for the dispatching and control of WoC in distribution networks, which will be capable of integrating such system platform and the intelligent algorithms which are elaborated in Section III to Section VI. In the later stage, we can attempt to implement engineering practice on the intelligent distribution network dispatching demonstration projects in China Southern Power Grid. Specifically, the explorations on system development and engineering practice of the WoC contain two steps as follows.

- Step 1: we need to establish a CPSS-based parallel system platform for the WoC. This parallel system is suitable for investigating of complex network theory and group game theory. Based on this platform, we can further develop a corresponding software platform for the intelligent dispatching and control system of WoC;
- Step 2: we need to search for some demonstration projects of smart grid, which can be used for engineering practice of the above platforms introduced in Step 1. Then, we should try to carry out some small-scale engineering application practices in order to verify and ameliorate the concept of WoC, together with its dispatching and control system and the CID methods investigated and discussed in this paper.

Specific explanations on the explorations in above two steps are briefly presented as follows.

A. EXPLORATIONS ON THE DEVELOPMENT OF A CPSS-BASED PARALLEL SYSTEM SOFTWARE PLATFORM FOR WOC RESEACH

In this section, we explore to develop a CPSS-based parallel system software platform for the smart dispatching and control of the WoC. Such CPSS parallel system for the WoC is also needed in Section III to Section 6 in this paper. Therefore, we deem that the development work of this software platform can be implemented on the self-developed smart grid integrated parallel computing and simulation platform based on multi-agent JADE (i.e., the Java Agent Development Framework), Matlab, and GAMS (i.e., The General Algebraic Modeling System). Among these, JADE is a multi-agent system platform that is developed based on Java language and compliant with the FIPA specification. Hence, we can use JADE to develop this parallel interactive software platform to realize clock synchronization between the physical system and mirrored simulation system during the digital simulation process, as well as parallel interaction of data in a real-time mode.

Moreover, we can use the Matlab and GAMS achieve hybrid modeling and programming, so as to implement third-party custom modeling and optimal power flow calculation of a multi-energy flow network. In particular, GAMS can be used as a powerful and advanced modeling system for mathematical programming and optimization to model networks with massive network nodes and solve the optimal power flow of underlying multi-energy flow; while Matlab can be used to implement intelligent learning algorithms programming and complex components modeling via the M-language.

Based on the functional components mentioned above, we have successfully constructed a CPSS-based parallel system framework for the comprehensive energy systems in 2017. This system can be used to train the group smart robots of energy control (i.e., RoboECs) which were proposed previously in [127]. The architecture of this system platform for laboratory investigation is demonstrated in Figure 24, where we have initially built a CPSS-based parallel system laboratory research platform for RoboECs in comprehensive energy and electric power system dispatching, control and management. In 2017, we deployed the Hadoop big data analysis platform on the developed smart grid integrated parallel computing simulation platform based on multi-agent JADE and Matlab/GAMS. This software system was tested in a key technology project implemented in China Southern Power Grid. This project uses Guangzhou Zhujiang New City as an Energy Internet technology verification system, with a computing scale of up to 70000 distributed equipment integrated (including photovoltaic, energy storage, flexible load and electric vehicles), 5000 grid nodes, and 200 nature gas network nodes. In this project, the software system interface and software functions we developed are shown in Figure 24. Therefore, we believe that this laboratory research platform demonstrated in Figure 24 for comprehensive energy systems and traditional power systems dispatching can be further

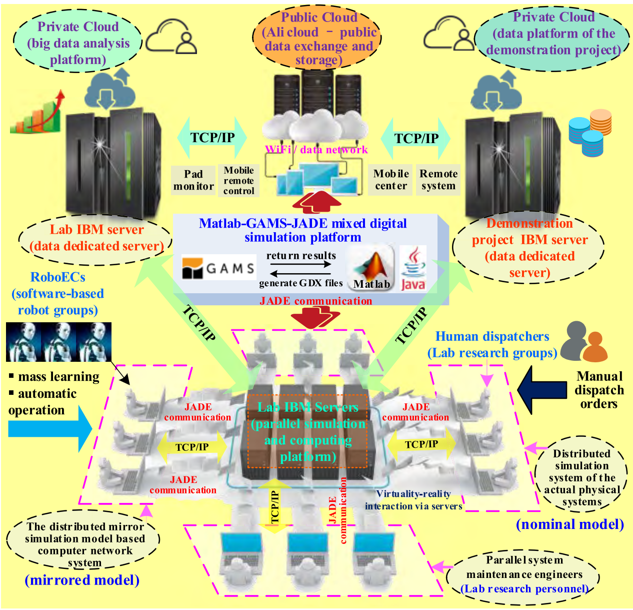


FIGURE 24. Architecture design of the CPSS-based parallel system laboratory research platform for RoboECs applied to comprehensive energy and electric power system dispatching, control and management.

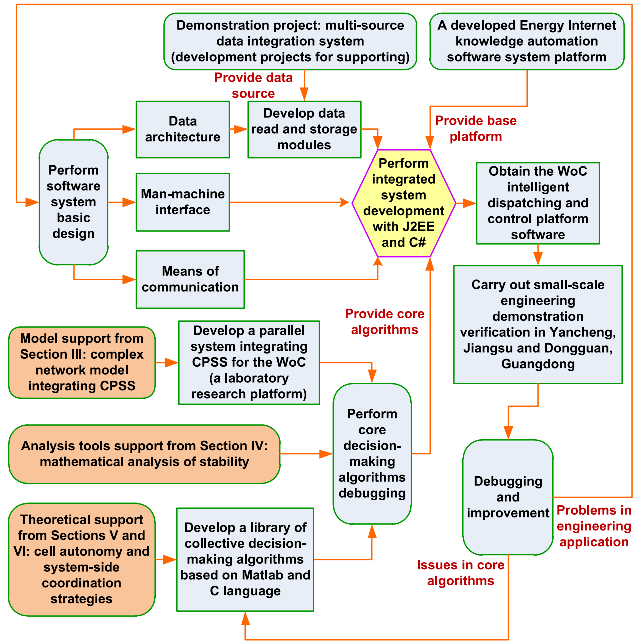


FIGURE 25. Architecture design of the CPSS-based parallel system laboratory research platform for RoboECs applied to comprehensive energy and electric power system dispatching, control and management.

expanded to a CPSS-based parallel simulation system for the collective intelligent learning of WoC system based on massive generation of samples in the future.

On the whole, we recommend taking two steps to develop the actual system for WoC. Step 1: we can attempt to build a parallel system for WoC integrating CPSS. This parallel system is suitable for the study of complex network theory and multi-agent stochastic game theory. Then Step 2: based on the developed parallel system simulation platform, we need to develop a software platform of intelligent dispatching and control system for WoC. More details on these two steps are demonstrated in Figure 25 as follows.

B. EXPLORATIONS ON VALIDATION STUDY BASED ON DEMONSTRATION PROJECTS

In this section, we explore to introduce how to conduct validation research work based on the demonstration projects. Addressed concretely, we can carry out investigation of demonstrated applications in a comprehensive energy demonstration area project which is being constructed by the authors in Songshan Lake Industrial Park, Dongguan City, Guangdong Province. This comprehensive energy demonstration area is presented as graphically in Figure 26, where the Songshan Lake comprehensive energy demonstration area is one of eight key Energy Internet demonstration projects which are being constructed by the China Southern Power Grid. Figure 26 shows only the first Energy Internet demonstration project implemented by the Dongguan Power Supply Bureau in Songshan Lake Industrial Park.

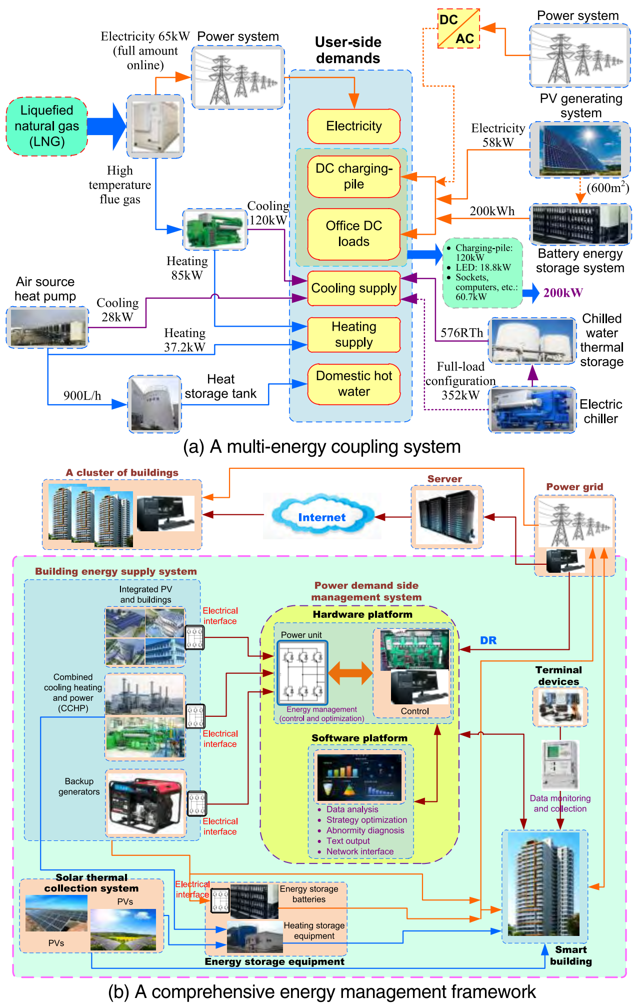
In next step, we will further conduct investigation of demonstrated application for the WoC in nine Energy Internet demonstration projects which are implemented by the Huawei Group, China Unicom Data Center, Guizhou Power Grid Corporation, etc. Among them, the aforementioned comprehensive parallel computing simulation platform for the smart grids has been deployed on a big data analysis platform (i.e., the Hadoop) in 2016, and used to conduct some engineering application researches in an Energy Internet-based comprehensive energy management demonstration project, as shown in Figure 27. This demonstration is selected in a university which is located in Guizhou Province.

In summary, we believe that the validation research on the WoC can be implemented via introducing the CPSS-based parallel architecture to the relevant practical demonstration projects which are being undertaken by the authors, such that relevant theoretical investigation work on the WoC can be conducted in the future.

VIII. SUMMARY AND PROSPECT

A. A BRIEF SUMMARY

In this paper, we have investigated the concept, theoretical methods, investigation objectives, and future challenges of WoC, with the goal of greatly improving the CID level of WoC dispatching and control system via new knowledge exploration and exploitation. Therefore, the theories of complex network self-organization evolution, multi-agent stochastic game, and PML-based CID for the WoC dispatching and control system are the highlights in this paper. Based on these, aiming at how to greatly improve the CID level of WoC through new knowledge exploration and exploitation, several key scientific issues to be solved in the future are investigated and discussed in this paper, from perspectives of WoC system, complex self-organization coupling network



(a) A multi-energy coupling system

(b) A comprehensive energy management framework

FIGURE 26. The architecture design of Energy Internet-based comprehensive energy demonstration in Songshan Lake Industrial Park, where (a) illustrates a complicated integration of the gas network, power network, heating network, and cooling network, which also involves user-side demand management, energy storage and clean-energy generation; and (b) demonstrates a framework design of comprehensive energy management for a cluster of smart buildings, which involves the building energy supply system, power demand side management system, energy storage system, solar thermal collection system, terminal monitoring system, cloud service, and power system.

modeling, EGT-based system stability analysis, cell autonomy, system-wide coordination, and software system development, and engineering practice. A brief summary of this paper is presented as follows:

1) We have investigated the concept of WoC proposed by ELECTRA, which can be seen as an enhancement of the novel concept of WoC proposed by ELECTRA. The WoC is a new smart grid framework whose weakly centralized new dispatching and control architecture can be regarded as a whole systemization of the micro-grid architectures. The ideological essence of WoC is decentralized autonomy and centralized coordination.

2) Based on the characteristics of WoC and actual engineering demands, aiming at how to greatly improve the CID level of WoC dispatching and control system via new knowledge exploration and exploitation, we have proposed, investigated and discussed two key scientific issues of the WoC to be solved in the future as follows.

The first is how to establish a self-organization coupling network model based on CPSS integration for the WoC to stimulate new knowledge emergence (i.e., new knowledge exploration stage), which is also a fundamental issue that needs to be addressed in the first place. We deem that this self-organization coupling network model concluded in the complex network theory is a significant model that requires in-depth investigations in the future. From this model, based on the principle of MSCDG, we designed the continuous and discrete CPSS-based complex network frameworks via integrating three categories of networks involved in a power grid, including its physical network, cyber network, and multi-stakeholder game network (i.e., social network). Moreover, we constructed a CPSS-based parallel system simulation model based on PML and GAN. A double coupling issue including external coupling and internal coupling needs to be solved in each of the above-mentioned three networks, such that the difficulties in modeling and technical challenges will be both high in the future.

The second is how to use the emerged new knowledge to greatly improve the global and local optimal dispatching and control decision-making level of WoC containing massive cells with characteristics of limited information, weak controllability, small capacity, and wide distribution (i.e., new knowledge exploitation stage), which is a core scientific issue to be urgently tackled in this paper, and also represents the final technical application achievements in the future. For this reason, we have conducted systematic investigations via integrating two levels, i.e., cell autonomy level and system-wide coordination level. During the investigation, collective ML and multi-agent stochastic game theory are significant theoretical tools. Moreover, we have combined the relevant investigations to be conducted in the future with the development status of power dispatching systems. Hence, we deem that the related theoretical research achievements must be recognized by the frontline electric power staffs. The investigation on this issue is the biggest scientific innovation in this paper, and it is also the most important key technical barrier that needs to be broken down in the future.

B. PROSPECT

In the future, we deem that one of the biggest technical challenges will be system development and technology demonstration of WoC. As stated previously, we have established a foundation for the development of an intelligent electricity distribution and utilization software system platform based on Energy Internet technologies, as well as a relatively solid foundation for engineering application. Hence, the conditions for a deep investigation of the WoC are relatively mature. However, it must be realized that the WoC is a brand-new system, instead of a simple and repetitive project development. This investigation requires integrated new theories and new

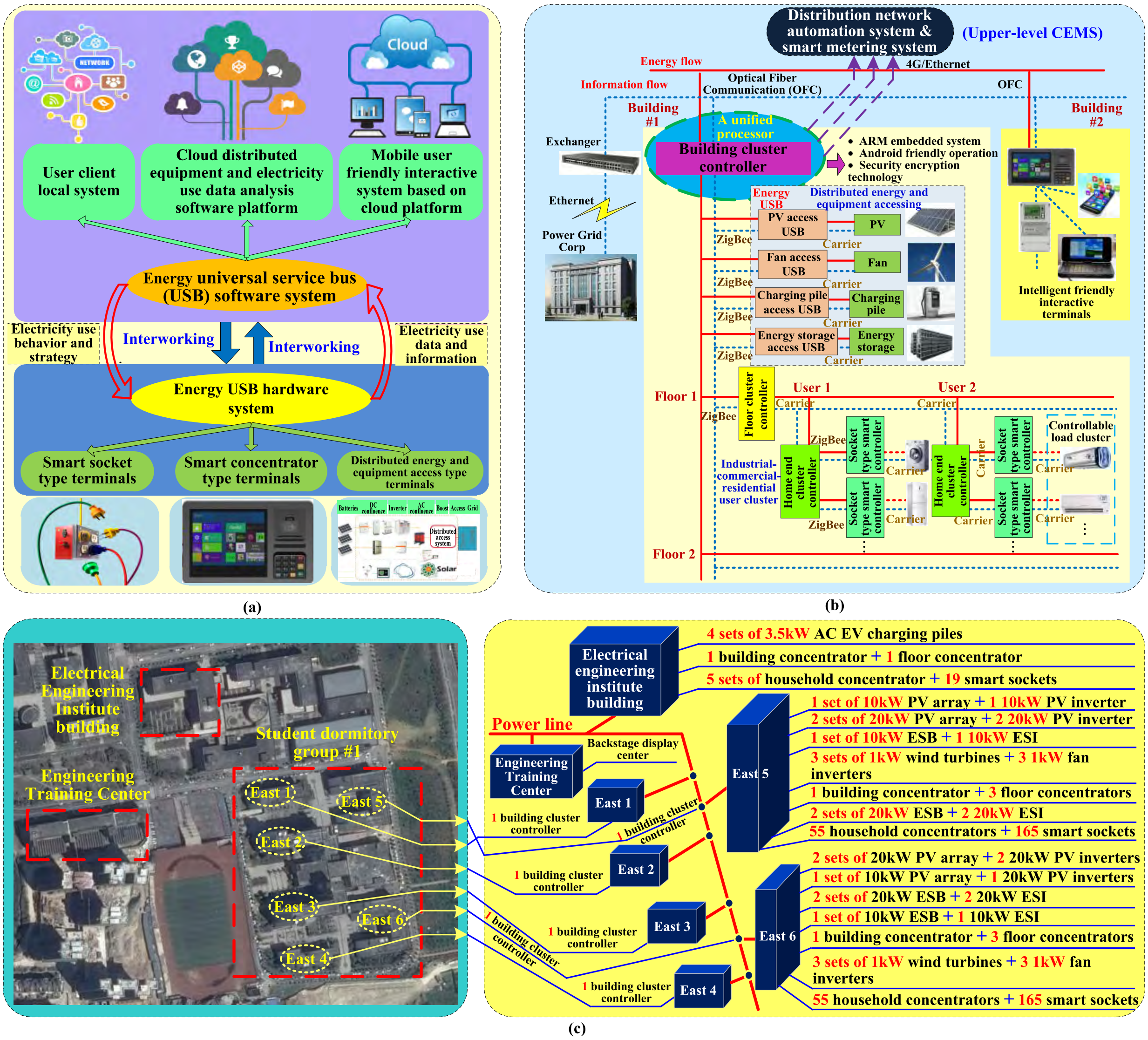


FIGURE 27. The sketch map of the Energy Internet-based comprehensive energy management demonstration project constructed in a university which is located in Guizhou Province, and among this demonstration project, (a) gives the overall system architecture design of the energy universal service bus (USB), (b) designs the application topology of the demonstration project, and (c) shows the overall design and installation drawings of the demonstration project application point in a university in Guizhou Province (where ESB and ESI represent energy storage battery and energy storage inverter, respectively).

research methods. Therefore, we deem that the difficulties in development of an actual system for the WoC must be overcome in the future.

Although the investigations on WoC in this paper are ahead of current status, i.e., the weakly-centralized control system architecture of the WoC is very different from centralized control architectures applied in current power systems, they are still promising because we have to face a fact and challenge currently and in the future that the dispatching and operation of power grid will more and more rely on high-penetration renewables, especially in the context of large-scale DG access to the power grid.

Taking China as an example, the National Development and Reform Commission, the two major Power Grid Corporations (i.e., State Grid Corporation of China and China Southern Power Grid), and the major academic groups in China all no longer have doubts about the above challenge. In China, this challenge is also an important direction for the Smart Grid Joint Fund Project Guidelines. Therefore, we deem that the technical risks that need to be minimized in the future are mainly how to progressively follow up the integrated construction of intelligent dispatching and control of the two major Power Grid Corporations in China, so that the theoretical results can be effectively linked with the application of technologies, and the frontline electric power workers can agree with them in practical projects.

Moreover, investigations on complex network theory have been carried out for decades, which have become more and more perfect. Based on the process of continuous interaction in a complex system consisting of massive agents, the individual linearity will evolved into overall nonlinearity, thus the group characteristics, nonlinearity features and complex system characteristics will emerge in a relatively stable phase, called new knowledge emergence. Therefore, only through the continuous system-wide interaction among cells in the complex WoC system and continuous local interaction between internal individuals in a cell, some new attributes and new phenomena (i.e., new knowledge) can emerge and be observed at the system level, thus facilitating a better insight into the nature of human market interactions. Currently, the research highlight of complex system theory is mainly focused at the theoretical level. Many scholars [54], [124]–[127] deem that, in the future, the parallel system will achieve a significant improvement and a remarkable progress in theoretical and application study of complex systems. Among this, the CPSS with cyber network, physical network and social network deeply integrated becomes the major and core issue which has been investigated and discussed in this paper. Although a large number of studies have been performed over the CPS, few investigations have involved the consideration of human and social factors. Hence, the introducing of human and social factors to the investigation of the large closed-loop system of the CPSS is the biggest highlight in this paper, which is also the biggest research challenge in the future. To answer it, we believe that the technologies of Internet and Energy Internet will be the key means.

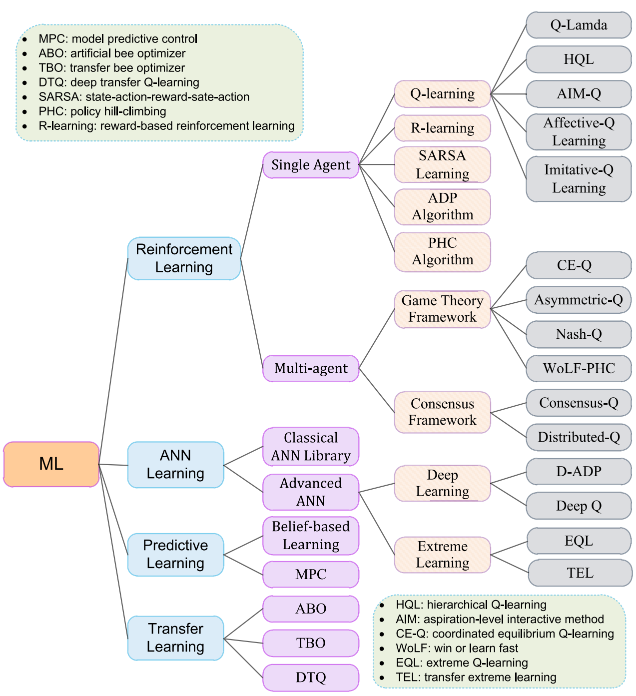


FIGURE 28. Establishment of a relatively complete library of ML algorithms by the authors based on the past fifteen years of research work on ML.

In recent years, many scholars have begun to use the technologies of Internet such as internet of things technology, big data technology, and cloud computing technology to conduct a research on the law of human and social behaviors. Among which, practical achievements have been very rich [64], [128]–[132]. Hence, based on these investigations, we believe that more and more relevant mature technologies will be adopted combining with artificial society modeling theories developed in recent years to conduct investigations on CPSS in the future. We deem that the risk of this research direction will be controllable and technically feasible.

In addition, EGT and group ML theory are hot topics currently at home and abroad, thus the mature theories and methods of which will build a strong foundation for investigation of WoC in the future. The related achievements of them are changing with each passing day. Based on these, we have preliminarily established a relatively complete library of ML algorithms, as illustrated in Figure 28. Therefore, we believe that the investigations on the WoC will be able to conduct at a relatively high starting level.

IX. CONCLUSION

The novel concept of WoC proposed by ELECTRA is a weakly-centralized new distributed hierarchical dispatching and control framework with features of high-penetration renewables access, self-organization coupling network structure, and collective intelligent decision-making. According to these features as well as actual engineering demands, aiming at how to dramatically improve the collective intelligent decision-making level of the WoC via new knowledge exploration and exploitation, this paper conducts a thorough investigation from the perspectives of complex network modeling, system stability analysis, independent cell autonomy, and multi-cell system-wide coordinated decision. In general, the main contributions of this paper are summarized as follows:

1) Based on a variety of advanced theoretical tools such as complex network theory, PML, parallel system theory, GAN, and multi-agent stochastic game theory, we systematically proposed the research content of the key technologies for the dispatching and control of WoC integrating CPSS, with the ultimate goal of developing a new generation of intelligent dispatching system with high-penetration renewables integrated under an open EM.

2) We explored in depth how to stimulate and utilize the new knowledge emerged from WoC through combining complex network theory, machine learning methods, and multi-agent stochastic game theory, in order to significantly expand the collective intelligent learning space, thereby greatly improving the collective intelligent decision-making level of the WoC system integrating CPSS.

3) We preliminarily discussed system development and engineering practice for the WoC, in order to form an intelligent dispatching technology system integrating theory, algorithm, software and equipment.

The biggest innovation of this paper lies in thoroughly investigating how to adopt complex network theory, PML and multi-agent stochastic game theory to stimulate and utilize new knowledge emergence to significantly improve the global collective and local independent decision-making levels for the dispatching and control of a WoC involving numerous cells with characteristics of limited information, weak controllability, small capacity, and wide distribution.

APPENDIX

$\boldsymbol{x}_i(t)$	state vector of the node i
i, j	the ith or jth node in a network
$\boldsymbol{f}(\boldsymbol{x}_i(t))$	continuous vector-valued function
Γ	inner-coupling matrix
c	strength of coupling
$\boldsymbol{A}_{\mathrm{EC}}$	external-coupling matrix of network topology structure
a_{ij}	the element on row i and column j of the matrix $\boldsymbol{A}_{\mathrm{EC}}$
$\boldsymbol{r}(t)$	transition probability of Markov chain
$\tau(t)$	time-varying delay
N	total number of nodes in a network
$\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{C}, \boldsymbol{D}$	Jacobian matrices of the non-linear function matrix after linearization
$\boldsymbol{f}(k), \boldsymbol{g}(k)$	non-linear function vectors in the kth iteration
τ_1, τ_2	time delays
$\boldsymbol{u}(k)$	control input matrix in the kth iteration
k	the kth iteration
l	the lth decision agent
π_l	probability distribution of state-action of the lth decision agent
$\boldsymbol{Q}_l^k$	knowledge matrix of the lth decision agent at the kth iteration
s_k	state of the multi-agent system at the kth iteration
$\vec{a}$	joint action of all the decision agents
a_l	action of the lth decision agent
L	number of the agents
$\vec{a}_{-l}$	joint action of all the decision agents except the lth decision agent
$\boldsymbol{A}(s_k)$	the agents' set of available joint actions in state s_k
$\boldsymbol{A}_l$	the lth decision agent's set of pure actions
a_l^{o}	the lth decision agent's any other action except the action a_l
$V_l(s_{k+1})$	state value-function of the lth decision agent in state s_{k+1}
α	knowledge learning factor
γ	discount factor
$R_l\ (s_k, \vec{a})$	feedback reward after implementing a joint decision-making action $\vec{a}$ under state s_k
m	the mth follower in a Stackelberg game
M	the total number of the followers in a Stackelberg game
$\bar{\boldsymbol{x}}_{\mathrm{g}}^*$	current optimal strategy of the leader
$\bar{\boldsymbol{x}}^*$	the joint optimal strategy of all followers
$\bar{\boldsymbol{x}}_i^*$	current optimal strategy of the ith follower
U_{leader}, U_i	the payoff functions of the leader and the ith follower, respectively
$\boldsymbol{A}_{\mathrm{leader}}, \boldsymbol{A}_i$	the decision-searching space of the leader and the ith follower, respectively
t, q, p	the tth follower who interacts with the mth follower, the qth real code for transfer learning, and the pth searching, respectively
M_m	the total number of followers who interact with the follower m
Q_{L}	the total number of real code for transfer learning
P_{S}	the total number of searching for the follower m
R_{mt}^{qp}	an immediate feedback reward, which can generally be transformed from the optimal objective
$\boldsymbol{Q}_{mt}^q$, $\Delta\boldsymbol{Q}_{mt}^q$	the knowledge matrix and its increment, respectively
q_0'	a random value in the unified probability distribution
ε	a parameter of local greedy searching
a_{rand}	the global random searching action
WoC	web-of-cells
CID	collective intelligent decision-making
ML	machine learning
PML	parallel machine learning
CPSS	cyber-physical-social systems
DG	distributed generation
EM	electricity market
EMS	energy management system
DR	demand response
NSFC	National Natural Science Foundation of China
ELECTRA	European Liaison on Electricity Committed
IRP	Towards long-term Research Activity Integrated Research Programme
CO	cell operator
TSO	transmission operator
DSO	distribution operator
MDP	Markov decision process
AI	artificial intelligence
ANN	artificial neural network
GAN	generative adversarial network
BPNN	back propagation neural network
SVM	support vector machine
ADP	adaptive dynamic programming
EGT	evolutionary game theory
IBC	Internet-based blockchain
MSCDG	Markov switching complex dynamic grid
PGE	power grid enterprise
EV	electric vehicle
NPSE	new power supply entity
EC	electricity consumer
AEG	asymmetric evolutionary game

GenCo	generating corporation
CPS	cyber-physical systems
MESS	multi-group evolutionary stable strategy
RD	replicator dynamics
ASEP	asymptotically stable equilibrium point
ESS	evolutionary stable strategy
VAPS	virtual artificial parallel system
ACP	artificial society, computational experiments, and parallel execution
PVC	primary voltage control
PPVC	pose-primary voltage control
IFC	inertia frequency control
FCC	frequency containment control
SVG	static Var generator
VSG	virtual synchronous generator
MPPT	maximum power point tracking
BRC	balance restoration control
BSC	balance steering control
AVC	automatic voltage control
FACTS	flexible AC transmission system
ROCOF	the rate of change of frequency
AGC	automatic generation control
PCC	point of common coupling
DEM	distributed energy management
CE	correlated equilibrium
VAS	virtual artificial system
FSEL	fast Stackelberg equilibrium learning
IES	integrated energy system
JADE	the Java agent development framework
RoboECs	robots of energy control
MPC	model predictive control
ABO	artificial bee optimizer
TBO	transfer bee optimizer
DTQ	deep transfer Q-learning
SARSA	state-action-reward-state-action
PHC	policy hill-climbing
HQL	hierarchical Q-learning
AIM	aspiration-level interactive method
CEQ	consensus equilibrium Q-learning
WoLF	win or learn fast
EQL	extreme Q-learning
NSGA-II	improved nondominated sorting in genetic algorithms
SPEA2	improved strength Pareto evolutionary algorithm
MGSO	multi-objective group search optimization

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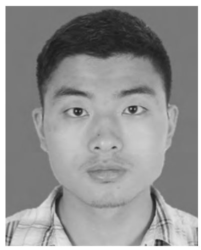

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