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Smart dispatching for energy internet with complex cyber-physical-social systems: A parallel dispatch perspective

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Summary
Energy internet (EI) is a complex coupled multienergy system; it is essential to investigate its multienergy dispatching optimization issues. To this end, this paper first proposes a novel conception of smart dispatching for EI with a complex cyber-physical-social system (CPSS) network from the perspective of parallel dispatch, called parallel dispatching robot (PDR), and investigates the implementations of PDR based on smart artificial society (SAS) modeling. First, we introduce EI and describe the dispatching issues of EI. Second, we discuss several important concepts supporting the parallel dispatch conception of EI, including knowledge automation (KA), CPSS, and parallel machine learning (PML). On the basis of these, we elaborate the concept of parallel dispatch. Moreover, we construct a large closed-loop feedback control framework of parallel dispatch for EI integrating a CPSS network based on KA and PML. Third, we establish an experimental platform for PDR research based on the proposed parallel dispatch framework. Fourth, we develop the PML-based SAS models of a single PDR in centralized dispatching modes and group PDRs in decentralized dispatching modes to achieve crowd wisdom emergence and performance improvement in current cyber-physical system frameworks of EI. Moreover, we design an external global closed loop for PDR to evaluate its operation stability. Lastly, we conduct a detailed discussion on PDR and offer some prospects for its engineering implementations. The biggest innovation of this paper lies in systematically proposing the smart dispatching concept and framework for complex CPSS-based EI from the perspective of parallel dispatch and thoroughly investigating how to use SAS modeling to implement parallel dispatching and control for EI considering human and social factors, which is a major extension and theoretical improvement to existing single smart wide area robot concept and a preliminary attempt in investigating a shift from Energy 4.0 to Energy 5.0 in China.

KEYWORDS
ACP method, AI, complex system theory, cyber-physical-social system, cyber-physical system, energy internet, parallel dispatch, parallel dispatching robot, parallel intelligence, parallel machine learning, parallel system theory, smart artificial society modeling, smart dispatching, virtual and real interaction

1 | INTRODUCTION

As global energy and climate crises worsened, various countries throughout the world are carrying out the practice and exploration of energy sustainability and low carbonization and have successively proposed the development goals and evolution routes of 50%, 80%, or even 100% renewables supply.[1-3] A new energy revolution is taking place and has drawn worldwide attention. The energy revolution, especially the rapid development of renewables and electric power, has profoundly changed the source and load characteristics of the power systems, posing great challenges to system operation.[4] Arguably, energy is an important material basis for economic and social development.[5] Moreover, human civilization development is closely related to the utilization of various energy resources.[6]

Energy transition in human energy utilization is accompanied by a tremendous leap in productivity and significant progress in human civilization.[7] We have recognized that global fossil energy resources are very limited. According to statistics,[7,8] as of 2013, the remaining proven recoverable reserves of coal, oil, and natural gas worldwide are roughly mined for 113, 53, and 55 years, respectively.[7] Moreover, these fossil energy resources are unevenly distributed around the world. In contrast, global clean energy resources are abundant. Based on statistics,[7,8] the global hydropower resources exceed 10 billion kilowatts, terrestrial wind energy resources exceed 1 trillion kilowatts, and solar energy resources exceed 100 trillion kilowatts. These far exceed the full energy needs of human society.

Faced with ever-expanding energy demands and deteriorating environmental problems, the good vision of energy internet (EI) represented by a new generation of energy and electric power systems (EEPSs) has been proposed by scholars as an emerging smart energy ecosystem for establishing a safer, more efficient, environmentally friendly, economical, and sustainable energy utilization model. The basic structure of EI is centralized by power grids integrated with high-penetration renewables and supported by advanced information communication technologies (ICT) and power electronics technologies, in which multiple energy networks (eg, cooling, heating, gas, and electric) are deeply coupled; thus, we need to achieve complementary and coordinated operation of multiple energy resources. The basic structural framework of EI is demonstrated in Figure 1, where EI consists of several energy local area networks (LANs) connected to each other.[9]

Generally speaking, EI has four characteristics,[6,7,9] ie, (a) renewable energy as the major primary energy source, (b) support the access of ultra-large-scale distributed generation systems and distributed energy storage systems, (c) wide-area energy sharing based on internet technologies, and (d) support the electrification of transportation systems. Therefore, EI is a dynamic research field with ubiquitous interconnection, peer-to-peer openness, low carbon, high efficiency, multienergy synergy, security, and reliability. Actually, EI is also a multienergy system with a complex cyber-physical-social system (CPSS) network,[6] in which information networks (ie, cyber networks), physical networks, and social networks are deeply integrated.

From the perspective of historical evolution of industrial development, the industrialization has gradually evolved from Industrial 1.0, Industrial 2.0, and Industrial 3.0 to present Industrial 4.0, ie, sequentially from mechanization age, electrification age, and information age to current internet age (see Figure 2A). It may even evolve into Industrial 5.0 in the future, and that will be a parallel era.[10,11] Meanwhile, the global energy systems are entering a new era called Energy 4.0 along with the development of industrial systems (see Figure 2B).[11] Overall, the evolution process of global industrial systems and energy systems are illustrated in Figure 2A,B, respectively.

In Figure 2A, the operation mode of Industrial 5.0 will lead the industry into the parallelism era.[12-14] In Figure 2 B, the Energy 4.0 is gradually considered to be a significant component of Industrial 4.0 and whose one of the most important technical features is smart energy plus the Internet, ie, the aforementioned EI. For instance, the "Internet +" based smart energy has been treated as a mainstream of Energy 4.0 revolution in China since 2016. Compared with conventional energy systems, Energy 4.0 systems have a high integration of both information and energy at the physical level, in which various types of high-penetration renewables such as wind power and solar energy are largely coupled and complementary.[11] Cyber-physical system (CPS) is a crucial component of Energy 4.0; thus, CPS has become an investigation highlight in the industry, energy, and electric power sectors.[5,6,12]

From the perspective of complex system theory, the CPS framework of current power systems is still established based on Newton's laws (see Figure 3A), causing that the predictions about the system behavior conducted by humans will not affect the results of power system operation. However, in the Industrial 5.0 or Energy 5.0 era, especially in the context of open and ever-growing energy and electric power markets, human and social behaviors, in essence, have deeply and widely influenced all aspects of the production, transmission, distribution, and consumption of energy and electric power industries. Consequently, we deem that the

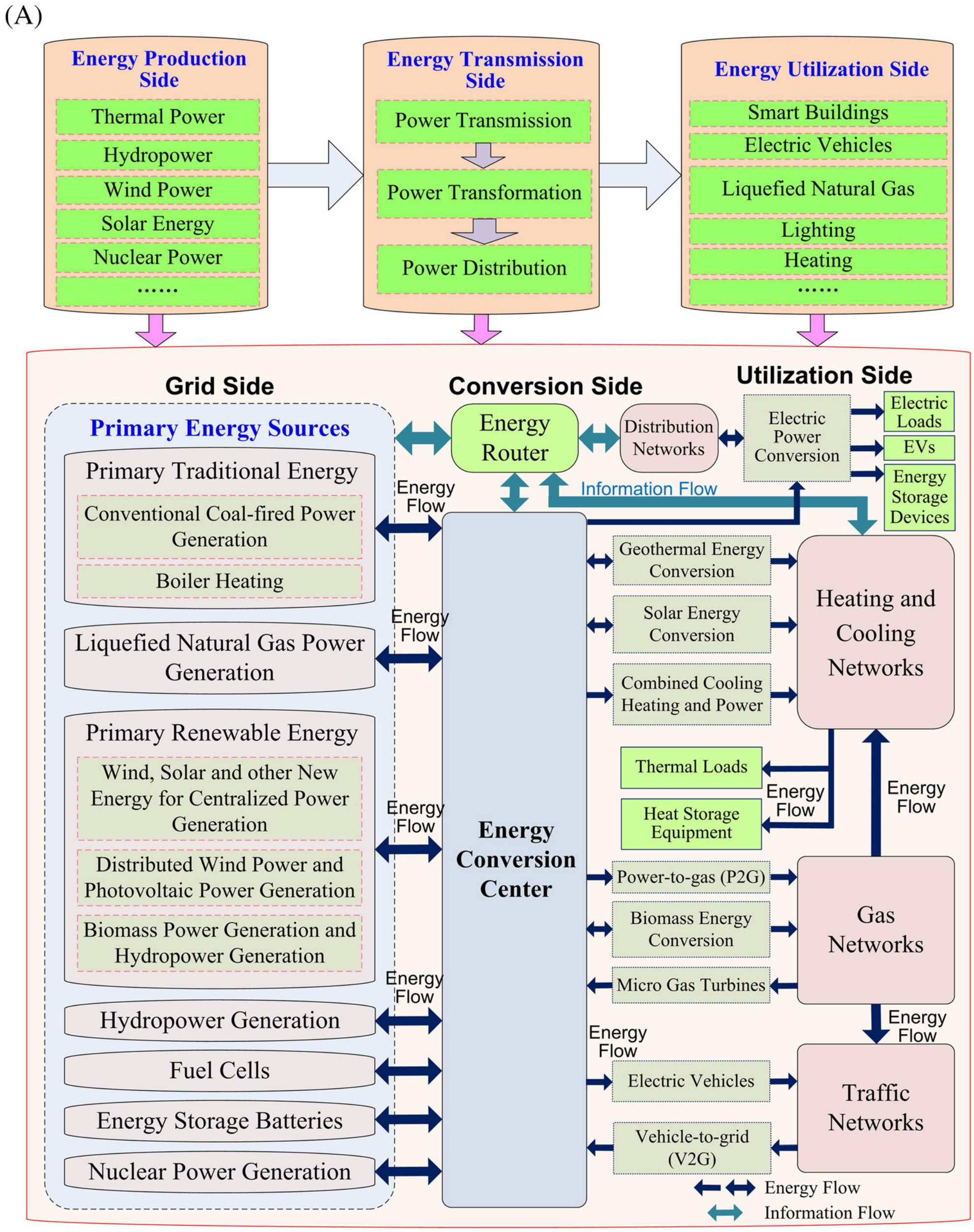

FIGURE 1 A basic framework and a typical application scenario of the EI. A, A basic framework of a typical EI system, in which energy flow and information flow are coupled with multiple energy forms on grid side, conversion side, and utilization side. B, A typical application scenario of the EI, where power grids provide AC and DC power generation for energy utilization such as industrial, commercial, and household users, energy storage, renewables utilization, and EVs, via transformer substations and energy routers [Colour figure can be viewed at wileyonlinelibrary.com]

engineering feasibility and practicability of CPS for a new generation of EEPS, ie, EI, remains doubted from the perspective of Merton's laws (see Figure 3B).[11,15] Hence, CPS may not be the ultimate form of EI. The difference between Newton's laws and Merton's laws (ie, the modeling gap between physical systems and artificial systems) is demonstrated in Figure 3C.[11]

The evolution of energy systems (see Figure 2B) is closely related to human civilization; besides, the mode of energy dispatching and control is also closely associated and coupled with human behaviors. Taking China as an example, a new round of electricity market reforms can be seen as another important reform initiative with far-reaching significance in China power industry since carrying out the 13th Five-Year Plan. Through revolution, it will become the norm for energy supply/service providers with independent incremental distribution networks and multienergy comprehensive control capabilities to complete energy procurement and sales through the transaction center. Due to the

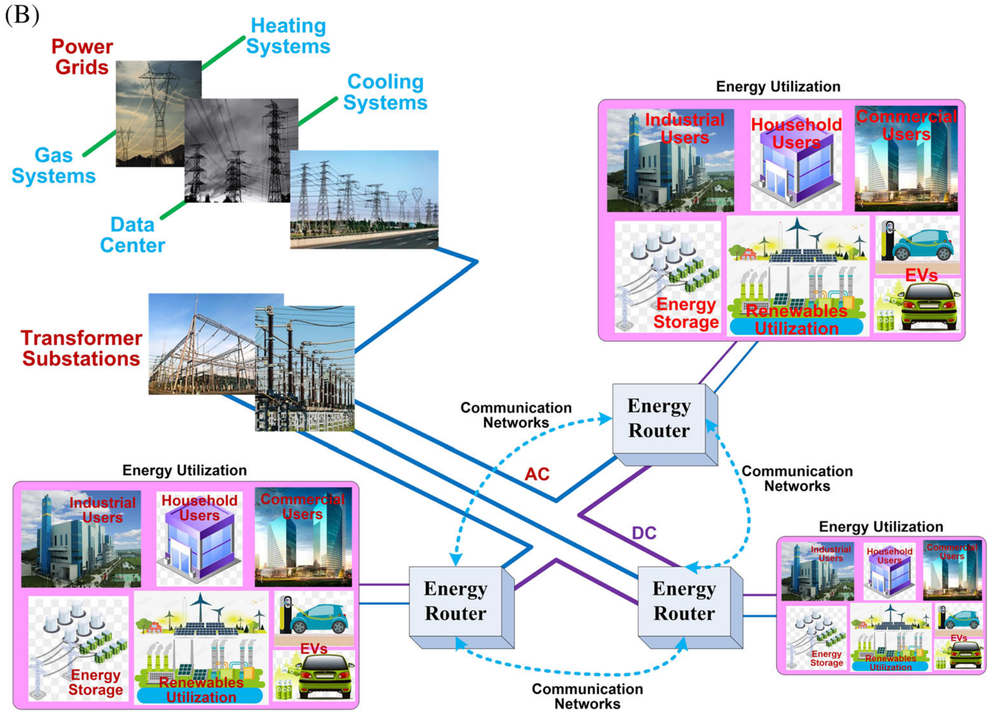

FIGURE 1 Continued.

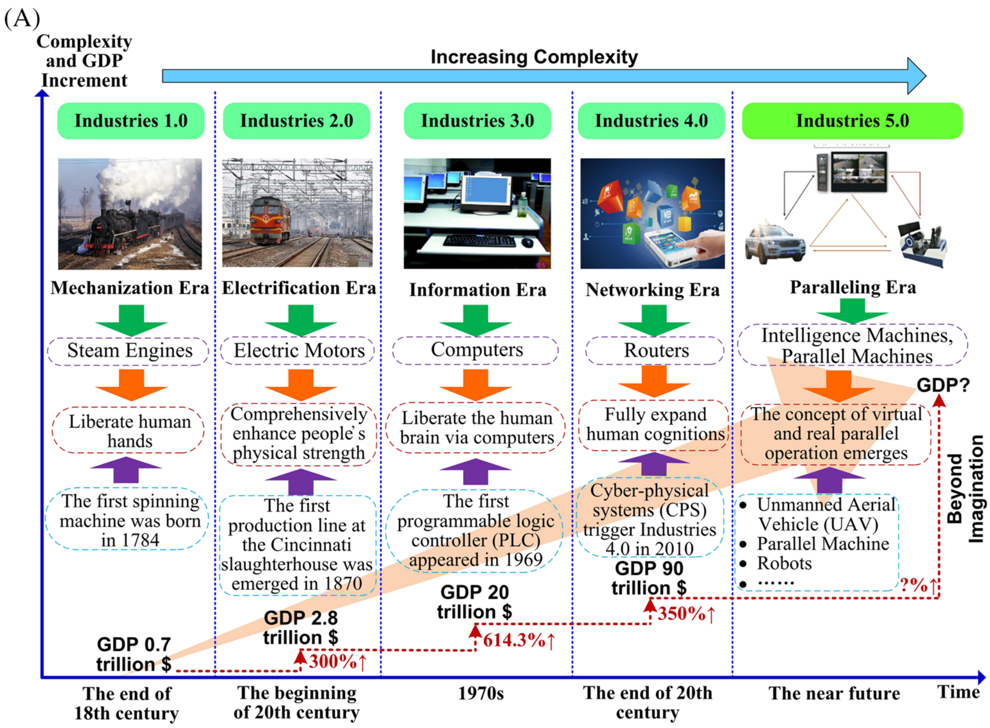

FIGURE 2 The illustrations for the evolution of global industrial systems and energy systems. A, The evolution process of industrial systems (this process of industrialization shifts from Industries 1.0 to Industries 5.0 in the future), involving the appearance marks, occurrence times, technical features, and global GDP of from Industrial 1.0 to Industrial 5.0. B, The evolution process of energy systems (this historical process of energy development shifts from Energy 1.0 to Energy 5.0 in the future), involving the energy times classification, dominant energy forms in each energy era, and the corresponding energy features [Colour figure can be viewed at wileyonlinelibrary.com]

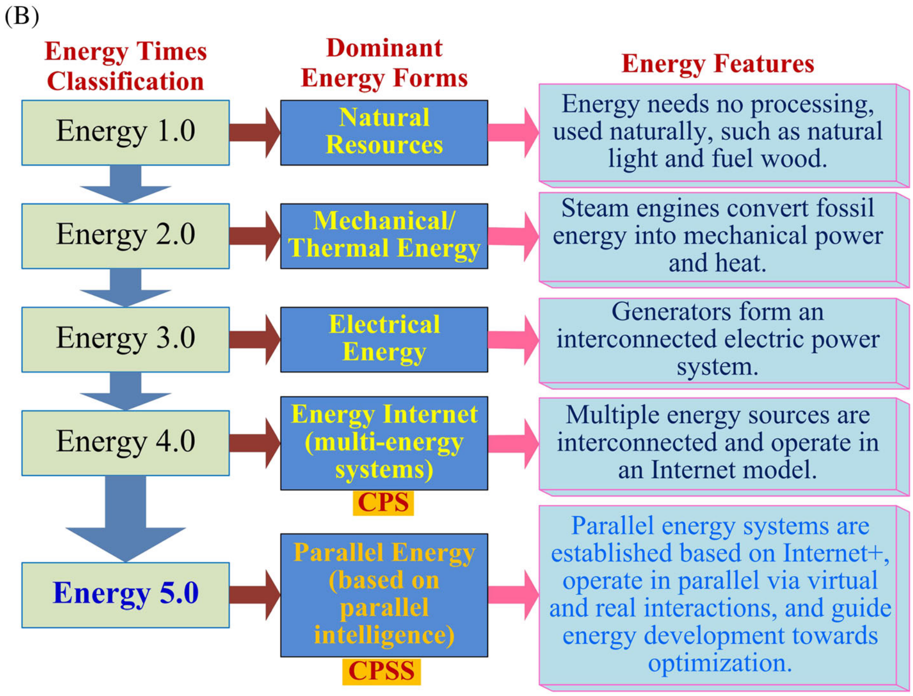

FIGURE 2 Continued.

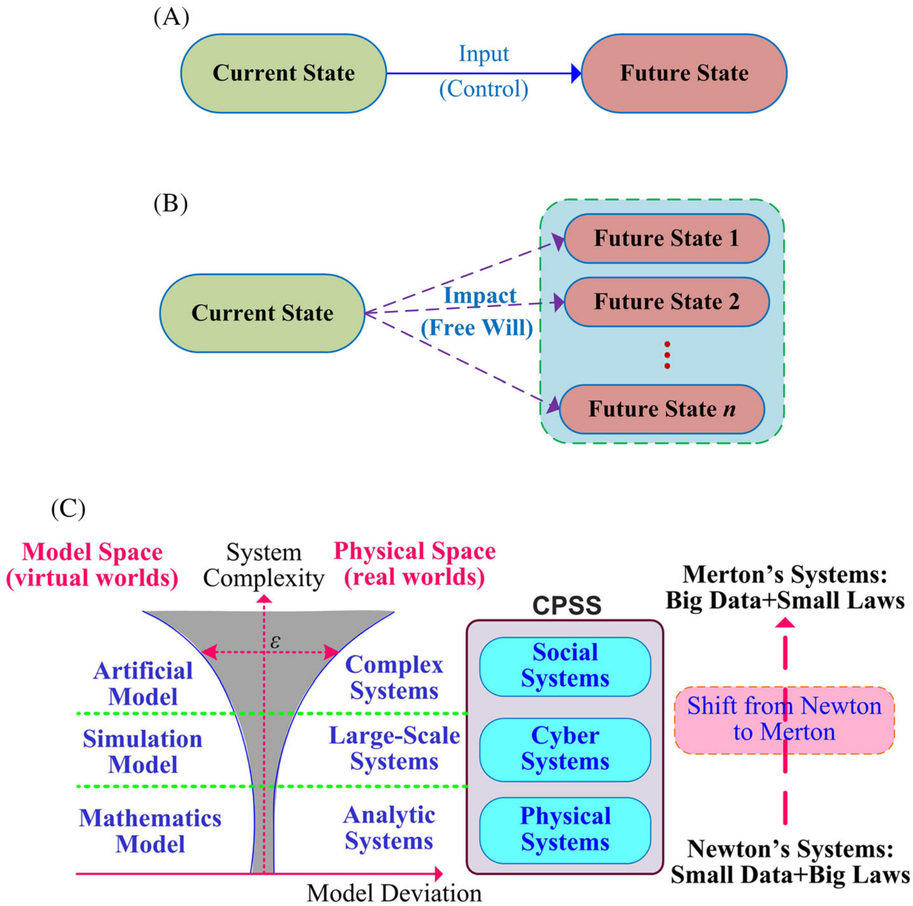

FIGURE 3 Newton's laws vs. Merton's laws. A, Newton's system controlling laws: Target implementation with certainty. B, Merton's self-fulfilling prophecy laws: Target implementation with uncertainty. C, The modeling gap between physical systems and artificial systems, where the shift from Newton to Merton means a shift from small data plus big laws in Newton's systems to big data plus small laws in Merton's systems [Colour figure can be viewed at wileyonlinelibrary.com]

increasingly higher distribution, diversity, and randomness of EI, the decision making of power system dispatch under planned market system will face challenges from market competition behavior with opaque information and higher uncertainty. Without considering the behavior of energy and power market and human dispatchers, we cannot find reliable and credible cyber-physical depth integration methods for current CPS. As a result, the power load forecasting results relying on Newton's laws (see Figure 3A) will also lose effectiveness; thus, it is essential to investigate the law of changes in EEPS under Merton's laws (see Figure 3B) from the perspective of complex system theory.[5,15] Figure 3C shows the modeling gap between physical systems (ie, Newton's systems) and artificial systems (ie, Merton's systems).

To this end, more and more researchers attempt to investigate the dispatching methods of multienergy systems under the background of EI. Among these, researchers from the Chinese Academy of Sciences cooperated with China Huadian Group, and they jointly pointed out that Industrial 5.0 following Industrial 4.0 will be emerged in the form of mass CPSS.[5,11] Although Energy 4.0 (which is seen as a crucial part of Industrial 4.0) has not emerged currently, the future energy utilization will be implemented based on CPSS, ie, the era of Energy 5.0.[5] In the era of Energy 5.0, a large amount of data will appear, and meanwhile, the cyber systems and physical systems will also generate massive data, leading to that it is hard to model in a traditional way and its 0simulation and control are also no longer suitable; consequently, there is an urgent need to achieve data speaking through knowledge automation (KA). Inspired by this, we construct a virtual parallel artificial system (VPAS) framework regarded as a parallel system in the framework of CPSS. This artificial system may be a sheer software-defined system, as presented in Figure 4.

The framework of CPSS proposed by Wang[10] needs a VPAS, as shown in Figure 4. This purely software-defined system contains two major subsystems, ie, one is a mirrored computational experiment system with self-correction capability, and the other is a KA system with capabilities of parallel learning and intelligent decision making. There is a parallel control layer between VPAS and actual system, through which we can achieve the integration of existing CPSs and human society systems, so as to realize a revolutionary transformation of controlled objects from control paradigm to guidance paradigm. For a small-size and isolated industrial production system, such as a chemical plant or power plant, it is technically feasible to develop its internal VPAS.[5,6] However, how to build a parallel system for the huge, open, and ever-growing EI will be very challenging. In such parallel system, how to fully describe the behavior of human dispatchers will become a practical and forward-looking scientific problem. Therefore, it is of great significance to design a CPSS-based smart dispatching and control system framework for the EI from the perspective of parallel dispatch.

The core idea of parallel dispatch is represented by parallel dispatching robot (PDR) based on parallel machine learning (PML) and parallel system theory. The PDR is implemented via a parallel control framework,[15,16] and such parallel control framework for complex cyber-physical-social EI system is developed based

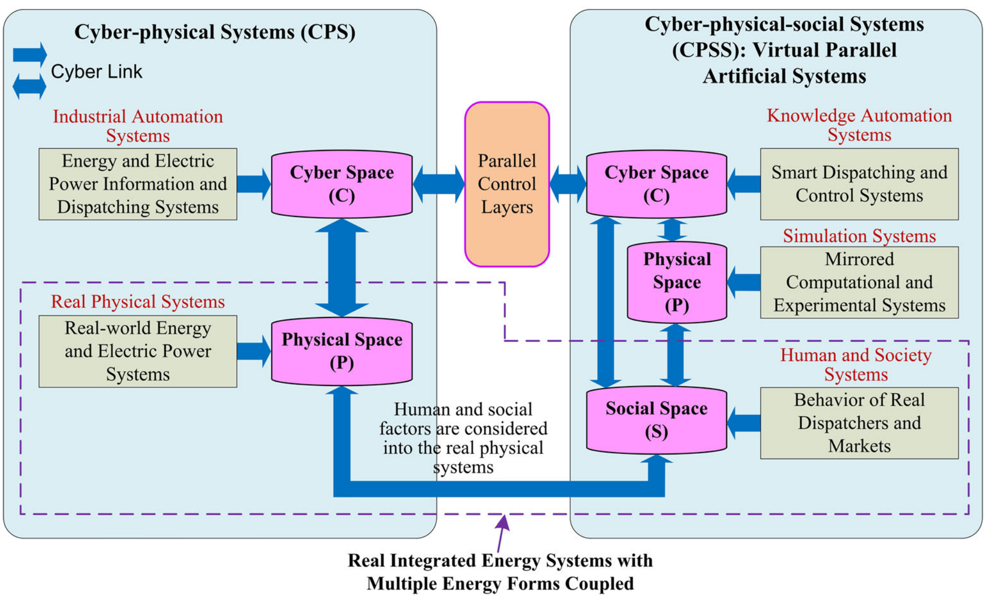

FIGURE 4 Design of a parallel CPSS framework for the smart dispatching and control of EI represented by a new generation of EEPS [Colour figure can be viewed at wileyonlinelibrary.com]

on ACP approach,[14] which means artificial systems (A), computational experiments (C), and parallel execution (P). Such ACP approach is first proposed by Professor F. Y. Wang recently,[14] which can be seen as a general methodology used for establishing and investigating the parallel dispatch model of complex EI systems.

Based on the above-mentioned parallel system theory and the ACP method, the final goal of parallel dispatch is to make decisions to drive the system in the real world so that it tends towards the parallel artificial system in the virtual world. In this way, the issues of complex EI systems can be simplified via utilizing VPAS (ie, a software-defined artificial system), such that we can finally achieve management and control of complex systems.

In the above-mentioned parallel control framework for complex EI systems, the parallel intelligence can be used in three operation modes, ie, learning and training, experiment and evaluation, and control and management. The process of such parallel control is a concrete embodiment of the KA process, and it is also an effective method for the KA and intelligent optimization of complex systems. Therefore, the idea of parallel control provides an effective solution for solving the optimization and control issues of complex systems. Inspired by this, the concept of parallel dispatch can be used in PDR for next generation of EEPS, ie, the EI systems. PDR is a concentrated expression of high intelligence in EI dispatching and control system.[17,18]

However, how to completely describe and model the dispatching behavior of human dispatchers? And how to develop an engineering feasible dispatching and control framework for the complex EI with a CPSS structure? These are practical and significant issues. To this end, we try to comprehensively propose a novel conception of smart dispatching for EI with a complex CPSS network from the perspective of parallel dispatch, called PDR (parallel dispatching robot), which can be seen as a centralized entity with high intelligence in the EI dispatching and control field. Aiming at PDR, this paper mainly focuses on elaborating its concept, framework construction, modeling, implementations, and future application prospects.

In this paper, we first construct a large closed-loop feedback control framework of parallel dispatch for EI integrating a CPSS network based on KA and PML. Then, we establish an experimental platform for PDR research based on the proposed parallel dispatch framework. The constructed control framework of parallel dispatch is an engineering feasible parallel dispatch framework in which human dispatchers and energy markets as social factors have been taken into account. Based on the parallel dispatch framework proposed and developed in this paper, how to implement PDR will become a key issue that needs to be addressed. This involves three aspects as follows.

a) How to achieve decentralized autonomy and approach multi-index optimization automatically via the group learning of dispatching robots is a scientific issue that needs to be focused on. To this end, the intelligent dispatching KA methods based on PML are one of the key technologies to solve this problem, which is mainly reflected in smart artificial society (SAS) modeling of dispatching robots. Besides, the multiagent game theory (especially evolutionary game theory) and complex network theory are another key theoretical tool to reveal the cooperative/competitive rules of group dispatching robots (ie, group PDRs). Therefore, it is crucial to combine the two key technologies for PDR research.
b) How to mathematically ensure that the dynamic process of interaction between the VPAS and real physical system is convergent? More precisely, under what conditions, can the used the artificial systems (A), computational experiments (C), and parallel execution (P) (ie, the ACP approach) guarantee the convergence of the large closed-loop system of CPSS containing social factors? This has always been the core issue of parallel system research.
c) How to improve the engineering practicality of PDRs is the last key issue to be concentrated on. To solve this problem, it is necessary to use the research results to explore the implementations on multienergy complementary demonstration projects to achieve small-scale verification results. This is an arduous but necessary step to move from theory to practice.

Therefore, aiming at the above three issues, in this paper, we comprehensively elaborate the concept of parallel dispatch for the complex cyber-physical-social EI, which involves several core concepts, including KA, CPSS, and PML. Moreover, we construct an engineering feasible parallel dispatch framework for the EI and design an experimental platform for PDR research based on the proposed parallel dispatch framework. In the proposed framework, for a single PDR, which can be seen as a centralized entity with high intelligence in the EI dispatching field, its KA process is essentially a process of relatively simple individual machine learning (ML) from dispatching information and dispatching processes; while the KA process of group PDRs is an automation process of more complex multiagent group knowledge decision making. This allows us to address simple issues independently via independent individual ML process and solve complex problems through collective PML. Thus, the KA process of group PDRs is essentially a generation process of group intelligence in a decentralized manner.

In addition, in this paper, we also thoroughly investigate the implementations of PDR (including a single PDR and group PDRs) based on SAS modeling. First, on the basis of the proposed concept of PDR and parallel dispatch framework, we introduce ML methods used in SAS modeling, as well as a PML method to generate massive training datasets for PDR. Then, we discuss the SAS modeling methods for the dispatching of EI with complex CPSS in two modes, ie, a single PDR in centralized dispatching mode and group PDRs in decentralized dispatching mode. Third, we propose a systematic method to design the external global closed loop in CPSS-based parallel EI dispatching framework. Moreover, we discuss its stability and system convergence based on the ACP approach. Lastly, we discuss challenges to be faced in the future development of PDR in the EI field and conduct prospects for future engineering implementations of PDR.

Overall, the major engineering value and scientific significance of this paper can be summarized as follows: We first comprehensively propose a novel conception of smart dispatching for the EI with a complex CPSS network from the perspective of parallel dispatch and thoroughly investigate its implementations based on SAS modeling, which is a major extension and theoretical advancement to the existing single smart wide area robot (Smart-WAR) concept and a preliminary attempt in investigating a shift from Energy 4.0 to Energy 5.0 in China.

The rest of the paper is organized as follows: We first introduce the concept of EI, comb the evolution of EI and EI policies, and describe the main forms of the future development of EI, as well as the dispatching issues that need to be addressed in the EI field in Section 2. Subsequently, in Section 3, we systematically discuss several important concepts covered in parallel dispatch of EI, including KA, CPSS, and PML. Based on these, we then elaborate the concept of parallel dispatch in Section 4. Moreover, we thoroughly investigate the framework construction of parallel dispatch in Section 5. Under the parallel dispatch framework, we first discuss the SAS modeling methods and develop corresponding SAS models for individual PDR and group PDRs in Section 6. In Section 7, we design an external global large closed loop for the parallel dispatch framework of EI, as well as two internal small closed loops. Furthermore, in Section 8, the challenges of developing the PDR in the future are discussed, and the prospects for engineering implementations of PDR are carried out. Finally, Section 9 concludes the main innovations of this paper. In addition, a nomenclature is contained in the end of this paper. The logical relation between the above sections is demonstrated in Figure 5.

2 | ENERGY INTERNET

2.1 | Definition of EI

The definition of EI has not yet been widely recognized. Some organizations have proposed different concepts and names for EI. Each of them focuses on different aspects. According to the characteristics of EI, these existing concepts regarding EI can be roughly divided into three categories,[19] as presented in Table 1.

As shown in Table 1, the first category is focused on global electric power interconnection and is represented by the Global Energy Internet proposed by China State Grid. The main feature is the expansion of power networks in space, interconnecting power grids from different regions, and achieving cross-regional consumption of different types of new energy in different regions. The second category is focused on multienergy integration, represented by comprehensive energy system, and the ubiquitous energy internet proposed by the Elman Neural Network Group. The main feature is reflected in interconnection of different energy systems such as electricity, gas, cooling, heating, and transportation networks. On one hand, energy efficiency is improved via comprehensive energy development and utilization. On the other hand, renewable energy is consumed by converting electric energy into heat, cold, natural gas, and EV energy storage. The third category is focused on integration of energy and information, represented by American Future Renewable Electric Energy Delivery and Management (FREEDM), German "E-Energy Plan," Japan "Digital Grid Plan," and the concept of "Energy Internet" proposed by J. Rifkin. The main feature is the use of power electronics, information communication, and Internet technologies for energy control and real-time sharing of information, such that realizing energy sharing and supply and demand matching and finally consuming the renewables.

2.2 | Evolution of EI

Generally speaking, EI has been developed since the 1980s. From a technical perspective,[10,11] the development process of EI is demonstrated graphically in Figure 6.

The initial concept of EI was put forward by R.B. Fuller in the 1980s, when he proposed the concept of world electrical energy grid, which was considered as the highest choice for energy.[20] In 1986, P. Meisen established the Global Energy Network Institute (GENI),[20] focusing on

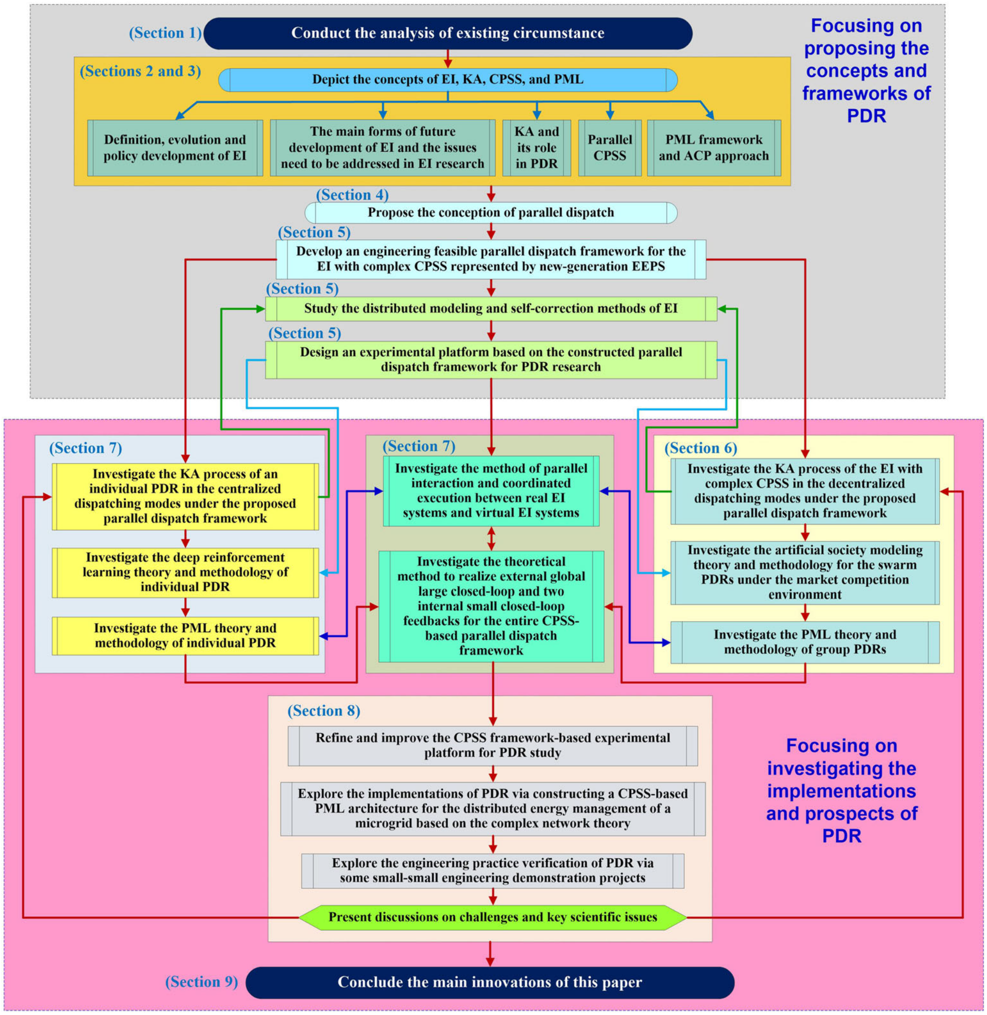

FIGURE 5 The logical relation between the sections in this paper [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 The category of existing EI conceptions

Characteristics	Representative
Focus on global electric power interconnection	✓ Global energy internet
Focus on multienergy integration	✓ Comprehensive energy system ✓ Ubiquitous energy internet
Focus on integration of energy and information	✓ FREEDM, E-energy, Digital Grid ✓ J. Rifkin's Energy Internet concept

power transmission network connections and renewables utilization.

After the US-Canada power outages happened on August 14, 2003, the journal *The Economist* published an article *Building the Energy Internet* in 2004 as the beginning of the development of modern EI,[21] which attracted the attention of scholars throughout the world.[19,22] In 2008, the US National Science Foundation funded the FREEDM project,[23] which lasted 5 to 10 years. This project established the FREEDM research center, and Professor Thomas of the center proposed and built the architecture system of the EI.[23,24] In the same year, the German Federal Ministry of Economics and Technology and the Ministry of the Environment jointly launched the E-Energy project, which lasted 4 years and implemented 6 demonstration projects of the internet of energy.[25] Meanwhile, Japan proposed the concept of digital grid.[26] In 2011, J. Rifkin from the United States built the architecture and basic features of the EI in his book *The Third Industrial Revolution*,[27] proposing that EI is one of the cores of the third industrial revolution, which makes EI more concerned and more influential. Prior of this, Rifkin has participated in energy planning in some European countries. In 2014, Rifkin published a new book named *Zero Marginal Cost Society*,[28] further expounding the role of the EI.

In China, since 2012, EI has been investigated by more and more scholars. In July 2014, the State Grid proposed the concept of building a global EI, and then in February 2015, the book *Global Energy Internet* was

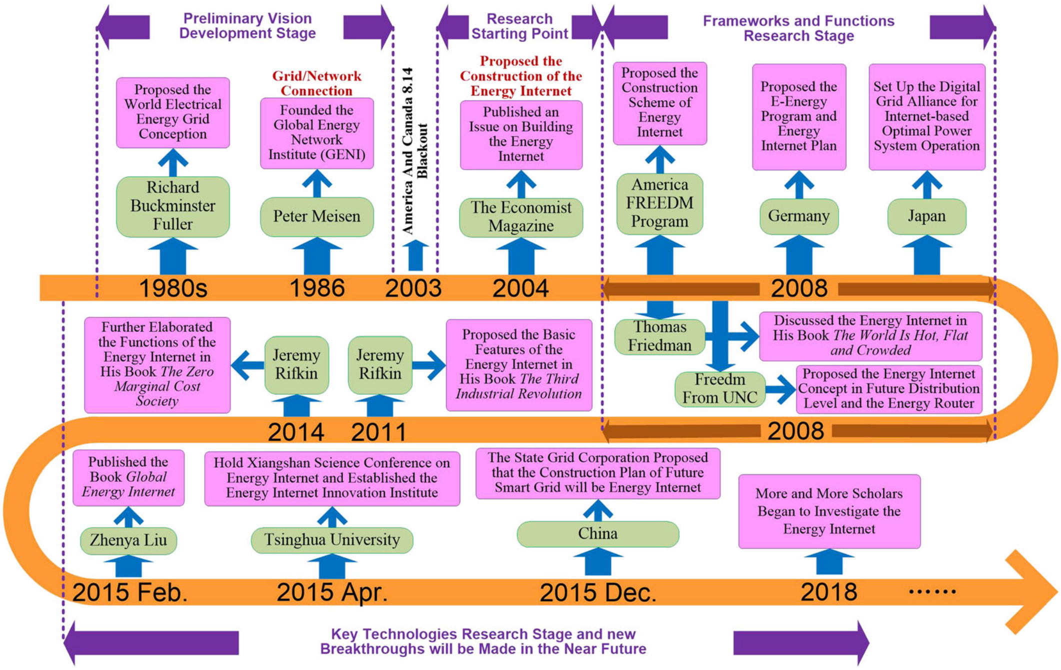

FIGURE 6 Historical process of EI concept development [Colour figure can be viewed at wileyonlinelibrary.com]

published.[7] In 2015, EI has been included in China's strategic emerging industries. Also in 2015, the China Energy Internet Academic and Innovation Alliance was established, marking the culmination of EI research. For instance, Zhou et al[29] deeply investigate the EI from a business perspective; Wang et al[30] conducted a survey on EI in aspects of architecture, approach, and emerging technologies; and Xue[31] investigated the relationship between comprehensive energy network and EI. On this basis, many scholars investigate EI from different technical and economic aspects, such as information technology, energy management, operation and planning, and market mechanism,[32-35] promoting the rapid development of EI throughout the world.

2.3 | Development of EI policies

In addition, while implementing technological innovations, some countries have gradually developed corresponding energy policies, providing opportunities for the vigorous development of the EI. For instances, the United States passed the US Energy Policy Act in 2005; the European Union adopted the Green Paper on Energy Policy in 2006 to encourage the sustainable use of energy, develop alternative energy sources, increase research investment in clean energy and energy efficiency, and promote the development of technology from a policy perspective.[36] In 2014, in response to climate change and reducing carbon emissions, the European Union announced the 2030 Climate and Energy Framework for Belgium,[37] further clarifying the need to increase the proportion of renewables and reforming the European Union carbon emissions trading system. In 2017, the Swiss referendum adopted Energy Strategy 2050,[38] which brought the Swiss energy landscape into a transition period. At the same time, other European countries have also successively adjusted their clean energy development policies. For example, the United Kingdom proposed the Clean Energy Growth Strategy, and Germany revised the Renewable Energy Law to further improve the utilization of renewables in electricity and transportation. It is conductive to promoting the complementary development of multiple energy sources and building a green, efficient, and safe energy system, which provides new opportunities for the rapid development of EI.

Along with the development of energy policy, the European Union has also formulated relevant policies in the energy trading market, such as Directive 2011/83/EU Decree,[39] which can protect the rights of energy consumers and further reflect the importance of consumers in the EI. In China, the government work report proposed the "Internet +" action plan in 2015, which greatly promoted the close combination of energy industry and the Internet, and clearly proposed to build "Internet +" smart energy and build a multienergy coordinated and complementary EI based on renewables such as solar energy and wind energy.[40] During the year of 2014 to 2017, the Chinese government focused on deployment and planning in specific areas such as microgrid, biomass energy heating, solar power generation and heating, and electric vehicle, further promoting the coordinated and complementary development of various distributed energy sources, realizing the intelligent production and use of energy systems through advanced information technologies, and rapidly promoting the implementation of EI from concept to practice.

2.4 | Main forms of the future development of EI

In recent years, we have conducted in-depth investigations on active distribution networks (ADNs), EI, and multienergy complementary integrated systems, and we have designed their overall system frameworks and corresponding optimized dispatching and control systems combining with engineering demonstration application projects. From these, we have recognized the engineering feasible demands from the engineering community for the basic innovation theories. Therefore, based on investigations in China, we deem that the cyber-physical fusion models, ie, CPS forms, of EI in China (which is represented by regional EEPS) will appear in two main forms in the next 10 years as follows:

1) *The primary form*: It is mainly represented by new constructions. Among these, the new constructed distribution networks, natural gas networks, and heating/cooling networks belong to an owner (ie, supplier and service provider), and they will be emerged in form of demonstration projects in many new development zones (eg, industrial parks, science, and technology parks). With further structural reforms of EEPS in China, the barriers to different energy networks will be eliminated eventually, and a group of energy suppliers/service providers will appear with property rights of multienergy networks; thus, they will have a unified integrated energy dispatching and communication center. These systems relatively own small scales, high cyber-physical integration, and simple social factors. Therefore, the Energy 5.0 system could be designed for them according to the engineering feasible architecture of parallel CPSS, which will be designed and elaborated in the next section.
2) *The secondary form*: It refers primarily to the reconstruction of stock projects. This means that the mutual transformation between ADNs and other networks (eg, gas networks, heating networks, and cooling networks) will be realized, and the decentralized and independent dispatching systems of the latter one will be gradually evolved into forms of centralized collaborative smart energy dispatching center. For example, Figure 7 shows a regional energy performance project implemented by us in Qianhai New District, Shenzhen, China, which is a novel integrated EEPS including a variety of coupled energy networks. Thus, such system is a typical complex CPSS. Although the property rights of the power networks, gas networks, and heating (or cooling) networks demonstrated in Figure 7 belong to different stakeholders, all of them reach a consensus that the effects of complementation and optimization of the multienergy systems will play an important role in improving system-wide energy efficiency. Therefore, these stakeholders will be positive to cooperate with each other to further overcome the barrier to each network under the guidance of the National Energy Administration and comprehensively consider the construction and planning of pipe and corridor networks into the future planning schemes. Thus, this will lay a firm foundation for the construction of a unified smart energy and electric power dispatching center in the future. Moreover, we have investigated the Guangzhou Development Zone and the Gui'an New Development Zone, from which we find that the forms of EEPS of them are very similar to the second form of the future development EI introduced in the previous section.

2.5 | Issues need to be addressed in EI research

Currently, electricity is the most widely used secondary energy source, and existing power grids have realized long-distance electricity transmission and distribution with a considerable scale. With the maturity and popularity of more and more electric equipment, such as electric vehicles, power resources will become the main form of energy directly used by people in the future, and the power networks will be a major component of the future EI. Notwithstanding, current EI policies introduced above propose intelligent consumption, promote the energy consumption revolution,[39] emphasize the flexibility of multiagent (including users) participation,[41] and advocate harmony between humans and the nature,[37,42] and so on, especially in the reform and promotion of the energy markets, implying that policy-makers have begun to pay attention to the importance of human participation in the development of EI. However, few investigations have included social systems into the EI, while the EI has become a more complex CPSS due to the tight coupling of multiple energy forms, especially the access of high-penetration renewables. Through survey, we find that most existing researches are concentrated at the technical, economic, and policy levels. There are few analytical frameworks and methods that consider the whole

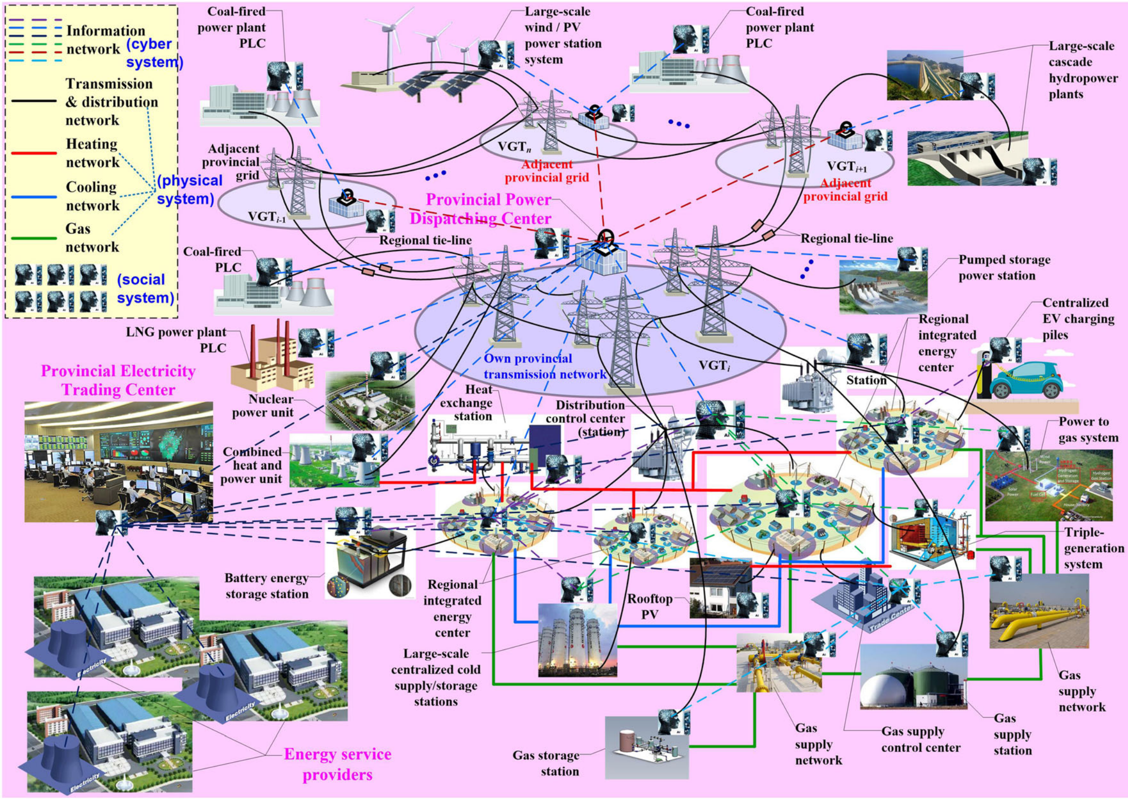

FIGURE 7 The framework of a regional energy performance project implemented in Qianhai New District, Shenzhen, China. In this framework, multiple energy forms are highly integrated and coupled, and the cyber system, physical system, and social system form a typical complex CPSS [Colour figure can be viewed at wileyonlinelibrary.com]

factors of technology, economy, policy, and environment from the perspective of human and society. Therefore, in order to investigate the EI from a more comprehensive, multilevel, and multiangle perspective, we need to pay attention to another important factor, the human and society, ie, we should investigate the dispatching of EI from the perspective of CPSS.

Therefore, an essential feature of the EI is the enormous emphasis on human subjectivity and the bidirectional interaction between humans and the system, ie, the EI should take people-oriented as a basic starting point in future development. There are different subjects in EI, including operational scheduling,[43] consumers, producers, regulators, and even vandals. Their behaviors and interactions will affect the operation, planning, supervision, and marketing of the EI directly or indirectly.[44] Therefore, it is necessary and important to investigate the dispatching of the EI from the perspective of human and society, ie, from a parallel dispatching perspective. The interaction between social systems and the EI is inseparable, making social systems become an important part of the EI. That is why we should not define the basic characteristics of the EI from a technical perspective and ignore its social attributes.

For this purpose, we attempt to investigate the dispatching of the EI from a parallel dispatch perspective, in which the social attributes are taken into account, ie, we seen the EI as a complex CPSS. KA is a crucial technology to realize parallel dispatch of the EI. In the next section, we will introduce the concept and key technologies of KA.

3 | SEVERAL IMPORTANT CONCEPTS SUPPORTING THE PARALLEL DISPATCH CONCEPTION OF EI

3.1 | Knowledge automation

1) Definition and importance of KA

The most intuitive definition of KA is the automation of knowledge work.[45] Actually, this is just a matter of translating the definition of KA into the definition of knowledge work,[15] and it cannot be used to reflect the full and essential meaning of KA. KA is a crucial technique to promote a transition from conventional energy paradigm to smart energy paradigm. The major difference between the two paradigms is reflected in intelligence, which is represented by plug-and-play of hardware systems and KA of software systems. Why do we need to develop KA techniques in modern society?

This is because the modern society as a knowledge era needs KA as like as the industrial era develops rapidly based on industrial automation. In the industrial era, humans need to develop industrial automation systems to implement, operate, and maintain various large-scale or sophisticated systems and processes. In the same way, faced with the internet of things, big data, cloud computing, intelligent technology, etc, the rapidly emerging knowledge era has also put forward higher and more presumptuous demands for human intelligence; thus, humans need to make up for this by means of KA, so as to complete various uncertain, diverse, and complicated tasks.[15]

Over the past two decades, the rapid development of the Internet, big data, and ML has made the KA technique more technically feasible. The year of 2016 can be seen as a milestone year for artificial intelligence (AI) and KA. In this year, a new computer program of Go named AlphaGo developed by Google's DeepMind team beat the world's top player Sedol Lee at 4:1. After that, the upgraded version of AlphaGo, called AlphaGo Master, defeated more than ten top professional Go players from China and Korean, including Jie Ke, the world's no. 1 Go player. Moreover, AlphaGo Master is incredible to create a win record with 60:0. The game of Go is commonly deemed as a typical knowledge learning and real-time decision-making process, which, traditionally, has been considered to represent the highest level of human intelligence. Therefore, technologically speaking, the victory of AlphaGo, AlphaGo Master, AlphaGo Zero, and AlphaZero indicates that KA can be used to replace many fields of the industrial automation system, where human interventions are required.

The victories of AlphaGo in 2016 and AlphaGo Zero and latest AlphaZero in 2017 have demonstrated that KA can be employed to replace the industrial automation systems in many application fields, where human interventions are required.[46-48] Taking AlphaGo Zero as an example, it is no longer constrained by the limits of human knowledge,[47] ie, it is able to discover new knowledge, develop nonstandard strategies beyond the scope of traditional Go (which is an extremely complicated board game) knowledge, and create new moves during its self-play training process.

Moreover, the economic impact of the automation of knowledge work will be even more astonishing. For instance, the McKinsey Global Institute predicted 12 disruptive technologies that are likely to determine the future economy by 2025.[45] Among these, the automation of knowledge work represented by intelligent software was ranked second.

As presented in Figure 4, the KA system, constructed based on intelligent decision-making algorithms from a parallel dispatch perspective, is seen as another key component of the framework of CPSS, except for the physical system. From the perspective of industrial automation, mechanical automation, electrical automation, and electronical automation, in essence, are all treated as automation of physical processes. On the contrast, the "Internet +" era is represented as the information automation and intelligence automation in the cyberspace, ie, the KA.[6,15,49]

2) Key technologies involved in KA

The key technologies of KA are knowledge representation and ML technique. Among these, the former, actually, is a process of transforming the abstract information (eg, processes and experiences) and unstructured information (eg, noises, images, and symbols) into the structured data, which is available for storage and logical calculation by computers. Therefore, knowledge representation is generally considered as a specialized discipline that combines computer science and mathematics and is also the basis of all AI technologies.

The key to implementing KA is to introduce the ACP method,[15,50,51] ie, artificial societies (A), computational experiments (C), and parallel execution (P). This is because during the modeling of dispatching for the EI from a perspective of parallel dispatch, the traditional simulation models and simulation systems are not suitable for the construction of virtual artificial world, resulting in that we need to adopt complex system analysis methods based on big data analysis, including the artificial system based modeling methods, computational experiments and system analysis and evaluation, and parallel execution and system control and management.[10,50]

3) The ACP approach to achieve KA

The ACP framework proposed by Wang et al[50-52] is demonstrated in Figure 8, where the core of ACP approach is to decompose the virtual parts of complex CPSS into quantifiable, computable, and executable processes. The three parts included in the ACP method are briefly introduced as follows.[5]

Artificial systems (A): based on the data collected from the real physical world, we can employ the data-driven and semantic modeling methods to construct the feedback from information to behavior according to the Merton's laws. For the data generated from the virtual

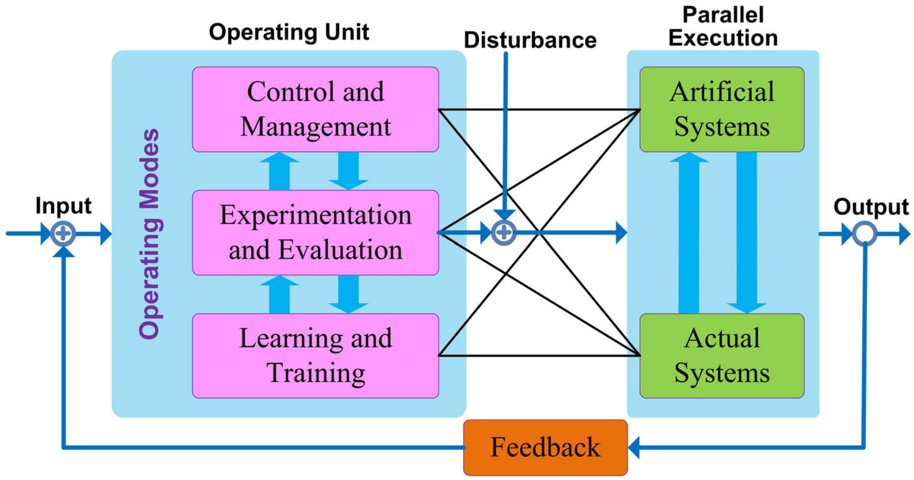

FIGURE 8 The ACP (artificial systems, computational experiments, parallel execution) framework for the control and management of complex systems, with the motivation to develop and organize AI methods and technology according to the structure of modeling, analysis, feedback, and management [Colour figure can be viewed at wileyonlinelibrary.com]

world, through data mining, the intrinsic value of mass information can be discovered, so as to achieve data driving.

Computational experiments (C): for the electricity prices and human social loads, few of them are available via statistical quantitative analysis, while most are difficult to be built as a numerical model; thus, we must use social computing methods to achieve that. Concretely, by integrating social computing approaches such as deep computing, collective pervasive computing, and historical experience computing, various models of the virtual artificial system can be obtained. The social computing must be implemented based on artificial society, ie, using AI for society modeling instead of traditionally using computers.

Parallel execution (P): the virtual artificial energy system and the physical energy system form a pair of parallel energy systems. Among these, the virtual and real interaction constitutes a new feedback control mechanism; the interaction between the physical process and the artificial computing process is implemented in a parallel way; and the solving is conducted through virtual and real interaction.

The steps of implementing ACP method including: (a) using artificial systems to model complex problems (physical, social, and cyber); (b) using computational experiments to analyze and evaluate complex phenomena; (c) combining artificial systems with actual systems and through virtual and real interaction, to guide and manage physical processes in a parallel execution way.[5,50-52]

4) The role of KA in parallel dispatch

For the implementation of parallel dispatch in the EI, KA is a crucial technique, which is mainly reflected in plug-and-play of the hardware systems and KA design of the software systems.[11,15] The parallel dispatch is represented by PDR. For the KA of a single PDR, it is a relatively simple process of ML of dispatching information and dispatching process by individual. In contrast, the KA of multiple PDRs is a quite complicated multiagent group ML process, ie, a decentralized generation process of group intelligence. It is found that few investigations are focused on the KA technique in the field of EI, which is a considerably large-scale and highly complex stochastic system.[27] Therefore, from the perspective of parallel dispatch, how to implement the KA of group PDRs will become a very challenging task to be faced in the future.

3.2 | Cyber-physical-social system

1) Defects of current CPS

Energy 4.0 systems, represented by EI, are typical CPSs involving an unprecedented integration of information systems and energy systems, while the role of humans as producers and decision makers are ignored. Furthermore, current investigations on modeling, analysis, and control of such CPS are not strictly carried out in accordance with the theoretical method systems of open complex giant system proposed by Qian et al.[53] Therefore, if we don't fully consider the influences of human behaviors and social attributes on the EEPS in the context of open, ever-growing and competitive energy electricity markets,[54] then the operation states of the EEPS with Energy 4.0 as the core will probably deviate far from the expected optimal operation points. That is why we need to consider the EI as a complex CPSS instead of CPS and integrate the decisions of real humans into the large closed loop of the EEPS. Hence, the parallel dispatching framework of the EI should be developed based on the CPSS, in which the virtual artificial energy system is introduced into the control of complex energy systems.

2) The way to construct parallel CPSS framework for EI

The basic of CPSS is massive data samples from the virtual and real worlds. The aforementioned Energy 4.0 and Energy 5.0 will be the big data era due to the generation of massive data samples, including social computing data, from the physical systems and artificial systems. Traditional simulation methods and control models cannot be used for modeling such a complex CPSS; thus, we need to use KA theory, method, and technique to deeply mine the intrinsic value of the data samples. This will be crucial for the construction of a virtual artificial system in the parallel system. For the scientific issues of CPSS, traditionally, the computing model and physical model are mutually independent, while a unified modeling theory is required in the modeling of CPSS,[5,15] in order to achieve the computing process, the dynamic interactions between physical systems and social systems, the consistency of time and space, and the processing of uncertainty, so that CPSS interacts and evolves, forming a parallel operation of virtual and actual systems. Therefore, the ACP method stated precisely will play an important role in the modeling of CPSS. By using the ACP approach, the complex virtual parts of the CPSS can be decomposed into quantifiable, computable, and executable processes.[5]

Therefore, we can use the ACP approach to construct an artificial associated system for the complex EI system (seen as a CPSS). After the actual system and artificial system are combined and interacted based on the ACP method, the resources and capabilities of the virtual and real subsystems will be integrated to form a new integrated system (ie, a CPSS) with superior overall functions and performance, so as to effectively manage and control the actual system. In order to realize the operability of ACP method, we need to construct an execution framework of parallel systems, as illustrated in Figure 8, where we need to inspect and evaluate via VPAS, and then continuously construct artificial models and repeatedly carry out computational experiments based on the data, so as to achieve parallel execution strategies.[5,15,50-52]

In the above process of parallel execution, the artificial system can be regarded as an extension of traditional mathematical or analytical modeling, called a generalized knowledge model, which is the basis for realizing agility to varying degrees. Generally speaking, the artificial system can be constructed as a multilevel intelligent model via the intelligent technique such as multiagent technique, so that the system can independently optimize the model according to the environmental conditions and its own states. The computational experiments included in this execution framework are the sublimation of simulations, which are the ways to analyze, predict, and select complex decisions, and also the means to ensure proper focus in complex situations.

In addition, the concept of parallel execution depicted in Figure 8 can be seen as a further extension of adaptive control and many management ideas and methods.[5] It is a new feedback control mechanism that is formed via the interactions between the virtual systems and real systems (ie, the interactions between the systems in the cyberspace and the systems in the real world). Hence, such mechanism can be used to guide actions and mark out targets, such that ensuring the convergence of the process.

Overall, for the parallel dispatching of the EI system with a complex CPSS network, the artificial systems, computational experiments, and parallel execution are the foundations of agility, focus, and convergence, which are effective control means of achieving ACP concepts vice versa. Therefore, according to the ACP method,[5,15] we can use the idea of ACP to achieve agility, focus, and convergence of the parallel dispatching system of the EI (a CPSS), so as to optimize the system and propose targets in various complicated situations, and finally achieve the goal via effective and specific control measures.

3.3 | Parallel machine learning

1) ML and its development in the EI field

ML needs to be conducted based on a better knowledge representation system.[55] With the improvement of computing power and the innovation of computational theory, scholars have made great progress in ML during the past 30 years. ML is attracting more and more researchers, and it has been successfully applied in numerous realms such as biology, medicine, EEPS, transportation, and environment. ML has become one of the most important branches of AI research,[56] as demonstrated in Figure 9.

In the field of EI, represented by EEPS, early ML methods (eg, BP neural network, support vector machine, and fuzzy sets) and their applications are hot research topics in the 1990s. During past 20 years, reinforcement learning (RL) algorithms as representatives of ML together with the Markov decision process (MDP) formed

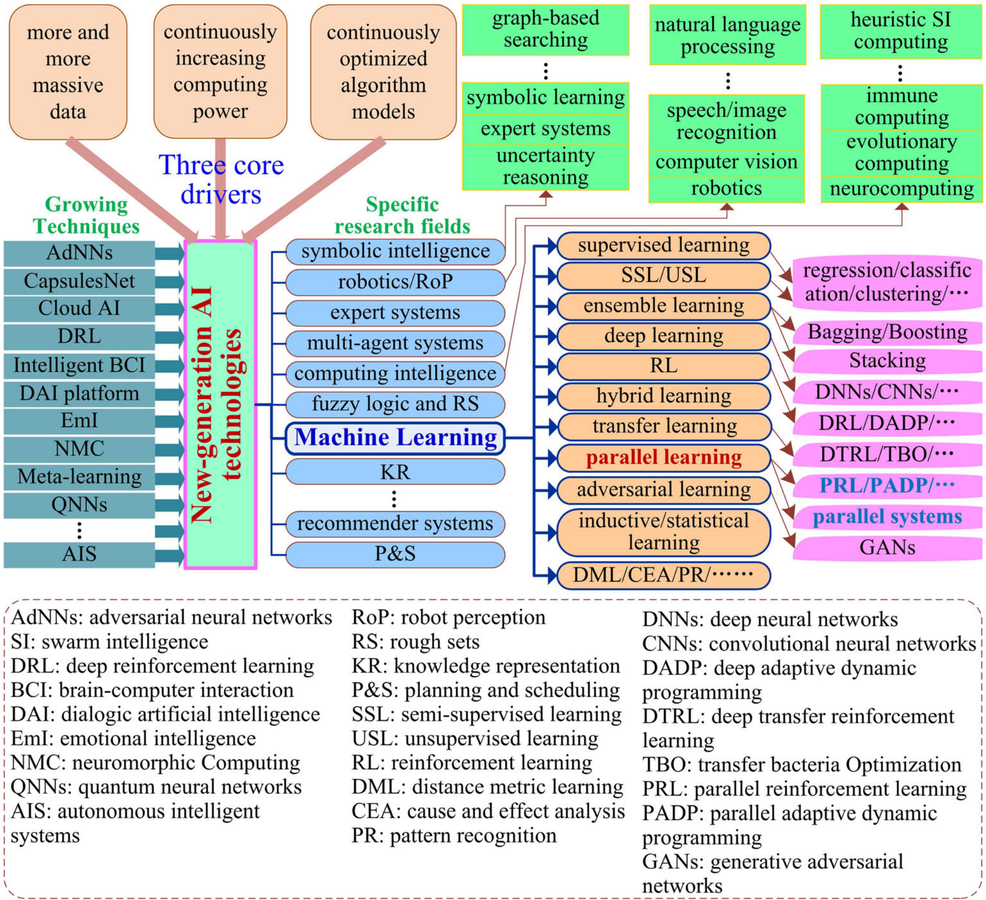

FIGURE 9 The research branches of current AI research, among which ML has become one of the most important branches [Colour figure can be viewed at wileyonlinelibrary.com]

the serious mathematical basis, and based on which, numerous new breakthroughs have been made in the field of ML. Some typical RL algorithms (eg, Q-learning, R-learning, adaptive dynamic programming [ADP], temporal-difference learning, and SARSA learning) have been introduced into the EEPS field. In addition, the integration of big data with some advanced ML algorithms such as deep learning, extreme learning, and hidden Markov model has once again been a hot spot in the research of EEPS.

We deem that the biggest challenge of ML is how to obtain the most valuable data samples for ML with minimum costs, especially when the target is a high-dimensional system. In such system, it is always hard to process complex data samples via traditional ML techniques such as RL, called the curse of dimensionality. Actually, the process of RL is the process of continuously updating the data tags. However, the efficiency of such learning is not so high, and it requires a lot of interactions with the environment to obtain feedback to update the model. In the face of big data processing in complex systems, too-high system state dimension often makes the exploration of feasible solutions very difficult, which is the so-called curse of dimensionality. In 2004, Professor Wang first proposed the parallel system ideology,[57-59] trying to solve the important issues in the socioeconomic system with a computational theory and method suitable for complex systems. The main idea of parallel system theory is to use large-scale computation to simulate, predict, and induce and guide complex system phenomena and form a new computational research system through the integration of artificial society, computational experiments, and parallel systems.[57-61]

Since 2015, Google's DeepMind team has published two articles in *Nature*,[46,47] making Deep RL (DRL) become the focus in the AI field. In 2016, the AlphaGo developed by DeepMind broke the myth that Go cannot be imitated by AI. Since then, the multilayer artificial neural network–based deep learning as perception together with the MDP-based RL as decision are becoming a pair of gold combinations of ML. However, the defects of traditional ML theoretical frameworks have been gradually discovered and confirmed by more and more scholars in the process of research and application. To tackle the obstacle, new theoretical frameworks of ML have been proposed successively. Inspired by the parallel system theory and AlphaGo stated above, Wang et al[60,61] try to extend the idea of parallel systems into the field of ML to establish a new theoretical framework to better solve the problems that traditional ML theories cannot solve well, such as data selection and action selection. Therefore, a novel theoretical framework of PML has been proposed by Wang et al.[60,61]

2) Principle of PML

In the CPSS-based dispatching framework of EI, the biggest highlight for ML of PDRs lies in adopting the latest theoretical framework of ML, ie, PML (or called parallel learning), which is first proposed by Wang et al.[60,61] Here, the theoretical framework of PML is demonstrated in Figure 10, where the parallel CPSS is used to generate a large amount of effective datasets, so that the ML capability of PDRs could be improved.

The theoretical framework of PML in Figure 10 is constructed based on the parallel system theory, which can be roughly divided into two mutual coupling associated stages. In order to make this framework better used for parallel dispatching in the field of EI, we have added a new stage to extend this framework to three stages as follows:

Stage I: the data processing stage. In this stage, we first use parallel learning to select the specific small data from the original data collected from the real physical EEPS (eg, operation modes, system parameters, and typical events) and the artificial society model. Then, the selected specific data is inputted into the software-defined VPAS for generating a large amount of new data. Lastly, the new data (ie, the artificial or synthetic data) together with the specific original small data are used to generate the big datasets to be learned by the machine for solving the issues, so as to complete the update of the ML model.

Stage II: the action learning stage. In this stage, the Q-matrix in RL theory is employed to implement knowledge storage, transfer, and utilization in a parallel learning mode, ie, the state transfer function is used to depict the dynamic changes of the system, as demonstrated in Figure 11. The parallel learning model is used to learn from the synthetic big data and store the learned knowledge into the system state transfer function. Particularly, the computational experiment methods are used to perform predictive learning via the parallel learning.[60] According to the extractions via learning, we can get small knowledge applied to some specific scenarios or tasks and then used for parallel control and parallel decision making. The small here refers to the specific intelligence knowledge needed to solve the specific problems, instead of the small amount of knowledge volume. Actually, as illustrated in Figure 12, the idea of using VPAS to generate a great amount of data is inspired by AlphaGo, which employs Monte Carlo tree search (MCTS) algorithm to implement self-exploration of the games[46]; thus, massive games of Go are produced via AlphaGo's self-play.[47] Hence, the number of Go games that really belong to humans has already occupied a very small proportion.[61]

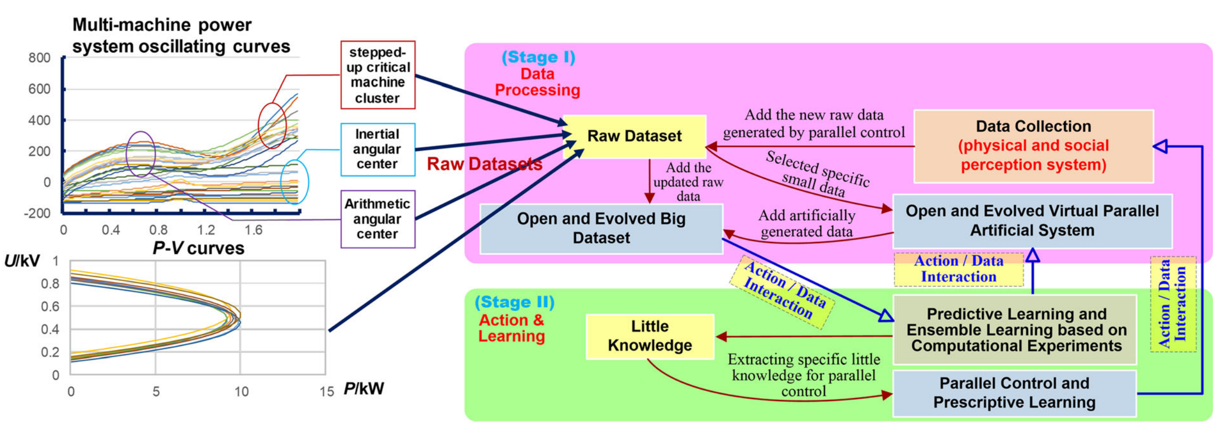

FIGURE 10 The theoretical framework of PML proposed by Prof. F.Y. Wang for collective learning of PDRs. In this framework, the left part is added by us, where the raw datasets come from the multi-machine power system oscillating curves, *P-V* curves, and so on. Thereby, based on these raw datasets and the principle of PML and parallel system theory, massive scenarios and data generation can be achieved [Colour figure can be viewed at wileyonlinelibrary.com]

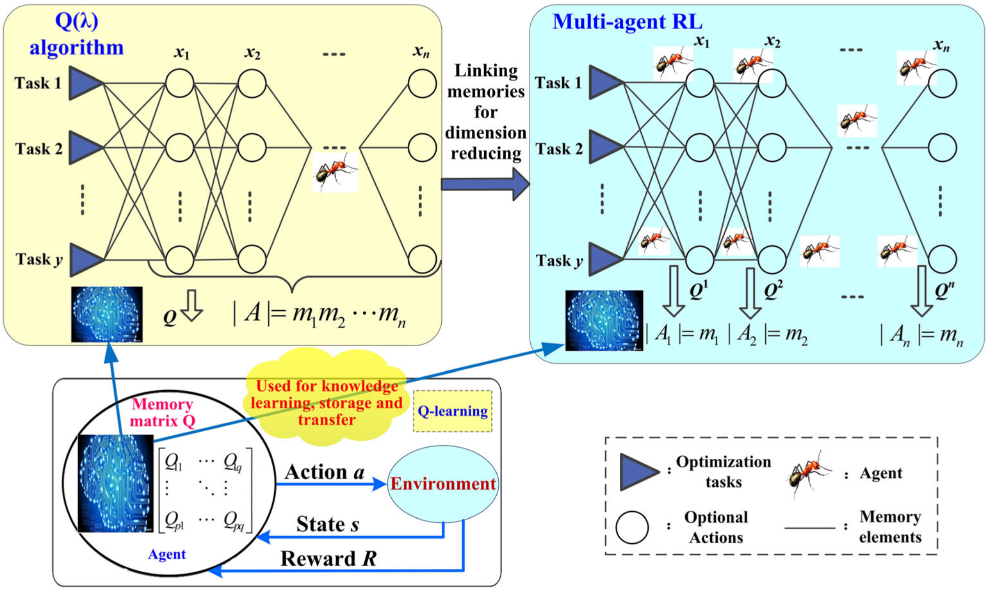

FIGURE 11 Advanced knowledge learning, storage and transfer in the decision-making process of dispatching. [Colour figure can be viewed at wileyonlinelibrary.com]

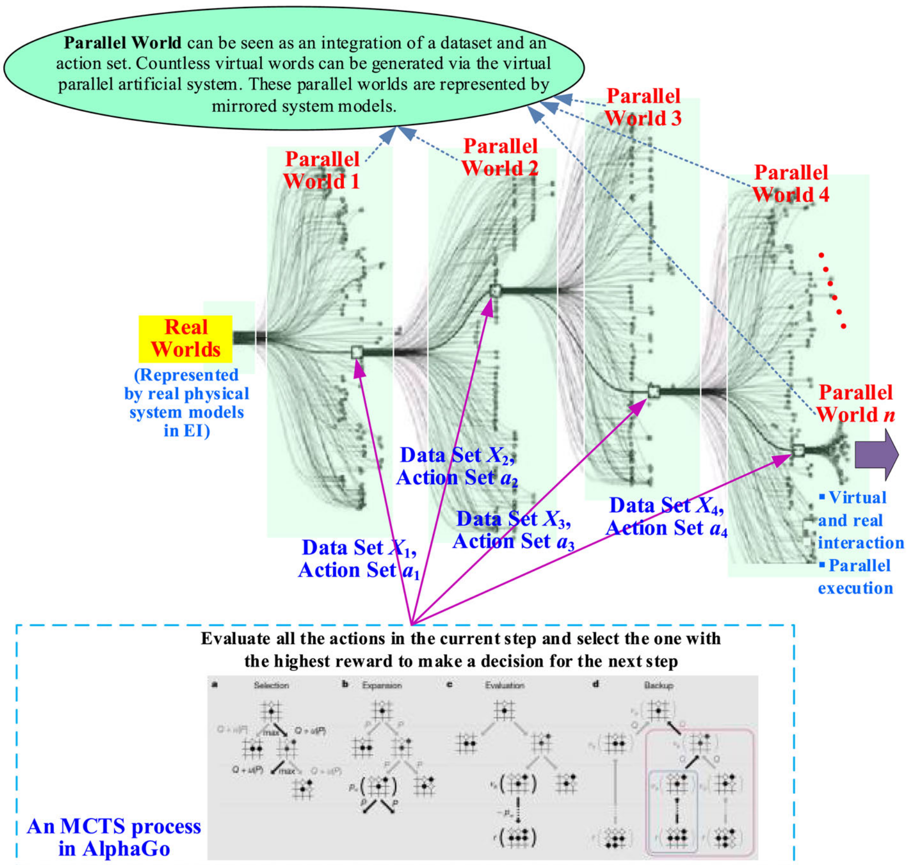

FIGURE 12 The mathematical descriptions for PL used in AlphaGo. Here, in order to address the current situation in a game of Go, AlphaGo uses Monte Carlo Tree Search (MCTS) method to perform several rounds involving tests of 20 to 30 simulation steps to explore the local optimal moves. This can be considered similar to the result of using mid- and long-term simulation iterations to predict and analyze the expected actions [Colour figure can be viewed at wileyonlinelibrary.com]

Apart from above-mentioned two stages proposed in the original theoretical framework of PML,[61] we add an additional stage in this framework, called Stage III, which is elaborated as follows.

Stage III: the data/action interactive enhancement stage. The EI system represented by EEPS will be an open and evolving system in the future; thus, the artificial system constructed in the CPSS-based parallel dispatching framework will also be open. The changes in the primary datasets and artificial system will lead to variations in the original datasets. Consequently, we need to add a new stage in the framework presented in Figure 10, and in this extended stage, the data/action is continuously kept active and enhanced. In essence, this new stage is also a process of retention and elimination of the big datasets.

Overall, through the parallel control and parallel decision making, the system will be guided to implement specific data acquisition, so as to obtain new raw data; and then, the new parallel learning is conducted again so that a closed loop between data and action is formed in the system. Moreover, Wang et al[61] introduced the idea of prescriptive learning into the theoretical framework of parallel learning, in order to recombine the data and actions from another perspective. Through the self-gaming of intelligent systems in the framework of parallel learning, a large number of new data samples are generated for ML; thus, ML has been shifted from the known training sample set (ie, a limited number of small data sample sets) to the era of acquiring massive imaginary training data samples (ie, an infinite number of big data sample sets) via self-exploration. This is a watershed for the AI to surpass the human intelligence.

4 | THE CONCEPTION OF PARALLEL DISPATCH

4.1 | Research desirability and basis of parallel dispatch

As stated preciously, Energy 4.0 is considered as an important part of the Industrial 4.0, and one of the most significant technical features of Energy 4.0 is the deep integration of smart energy and the Internet; thus, Energy 4.0 is a representative cyber-physical-energy system (CPES).[62] The high degree of integration of information systems and energy systems is emphasized in the CPES, while the role of humans as producers and decision makers is not considered in the energy systems. Furthermore, it is not strict to carry out investigations of modeling, analysis, and control in CPES according to the theoretical method system of open complex giant system proposed by Qian et al.[53] Therefore, the operation states of the EEPS with the Energy 4.0 (represented by EI) as the core will probably deviate far from the expected optimal operation points on the premise that we have not fully taken the influences of human behaviors and social attributes into account in an open, ever-growing and competitive energy and electric power market environment. Therefore, it is urgent to consider the role of humans and society and introduce the decisions made by real humans into the large-scale closed-loop system of the EEPS.

Recently, this has gained keen research interests from some famous energy research institutes and scholars. Among the investigations, Wang et al[57-59] first proposed the concept of parallel system with its methodology in 2004, and then combined which with AI and the Internet technologies to further put forward the concept of CPSS.[10] The concept of CPSS has been extended to the fields of EEPS, petrochemical industry, and urban traffic by Wang et al[5,13] successively. Very unlike CPS, CPSS is required to model with a unified modeling theory in order to realize the computing, dynamic interactions between physical system and social system, consistency of time and space, and solving of uncertainty issues,[63] so that CPSS can evolve interactively to form a virtual parallel operation mode together with the actual systems.

The emergence of CPSS and parallel system provides a powerful tool for the small dispatching of the EI from a parallel dispatch perspective. However, the relevant research work on CPSS and parallel systems is still in its infancy; thus, how to construct the parallel CPSS framework for the huge and open EI with multienergy coupling and complementary systems is still a highly difficult task. With the rapid development of AI, the Internet technologies, and big data techniques, the third industrial revolution will be inevitably promoted based on automation of human knowledge processing. This is the process of AI gradually replacing real humans, as well as a kind of software automation based on independent decision making of the machines.[15] For the dispatching field of EEPS, the process of software automation has started since the computer dispatching automation systems were born.

4.2 | Evolution of smart dispatching in EEPS field

In the traditional dispatching and control systems, a centralized control framework founded by T.E. Dy-Liacco,[64] known as the father of dispatching automation, in the late 1960s is generally employed. However, this framework is mainly constructed by experience and analysis, such that it cannot adapt well to the ever-growing complexity of power systems due to its low degree of automation and intelligence.[64] Since the 1990s, electric power companies have gradually adopted AI technologies to improve the decision-making capability of power grid dispatching.[65] Among these, Electricite de France (EDF) studies the application of rule-based decision tree and knowledge-based expert system in power grid stability assessment and decision making.[66] The Empros Power Control Center in the United States attempts to apply intelligent tools to the energy management system (EMS) at the time.[67] The Scottish Power Company adopts the iKue solution to sort out the experiences of the dispatchers and engineers as knowledge, achieving transfer of knowledge within the organization.[68] In addition, the United States PJM Company consecutively proposes the concepts of advanced control center (AC2) and perfect dispatch (PD).[69] During the development of EEPS dispatching system, scholars have gradually reached a consensus that conventional dispatching system used in the EEPS with human dispatchers as the core will be inevitably replaced by smart dispatching systems characterized by deep situational awareness capabilities and higher AI levels.[70,71] Therefore, the PDR developed based on AI and other advanced technologies as the ultimate form of smart dispatching will be a centralized entity of high intelligence of the dispatching and control system in EEPS.

For this purpose, the father of dispatching automation, Dr Dy-Liacco firstly proposed the concept of automatic operator (AO) in 1997.[17] AO is believed to be an embryonic form of the dispatching robot concept. The aim of AO is to achieve meticulous dispatch and improve the transmission capability of power grid through enabling the dispatching and control system to adapt to the online operation mode according to its automatic learning ability.

In the 21st century, aiming at the overall framework construction of the smart grids, the State Grid Corporation of China and China Southern Power Grid (CSPG), together with prestigious Chinese universities (eg, Tsinghua University), have made a series of great progress in smart dispatching and control.[6,70-77] Among these investigations, Xue et al[77] proposed a multiagent-based sand-table simulation (scenario planning) model, which can be regarded as an important attempt in the field of EEPS dispatching, as well as an application case of the man-machine combination-based Hall for Workshop of Metasynthesis Engineering (HWME), proposed by Qian et al[53] in the field of power systems. These investigations above have greatly promoted the application of AI technologies in EI dispatching and control,[65] especially in the field of EEPS. For instance, Lu et al[18] proposed a novel concept of Smart-WAR in 2011, which is constructed based on the hybrid control system for power system, as demonstrated in Figure 13.

However, we have to confront the fact that multiple energy networks in the field of EI are increasingly interconnected along with massive distributed new energy resources access to the power grid.[33,78,79] As a result, the pure power system EMS has been gradually transformed into forms of a comprehensive EMS (CEMS) in which multiple energy networks (eg, electric power, gas, heating, cold, and energy storage) are largely interconnected and coupled in a complementary manner. Comprehensive EMS has been gradually widely used in the field of EI with high-penetration of renewables. To this end, ETH Zürich first proposes the concepts of energy hub and energy interconnector, as well as the

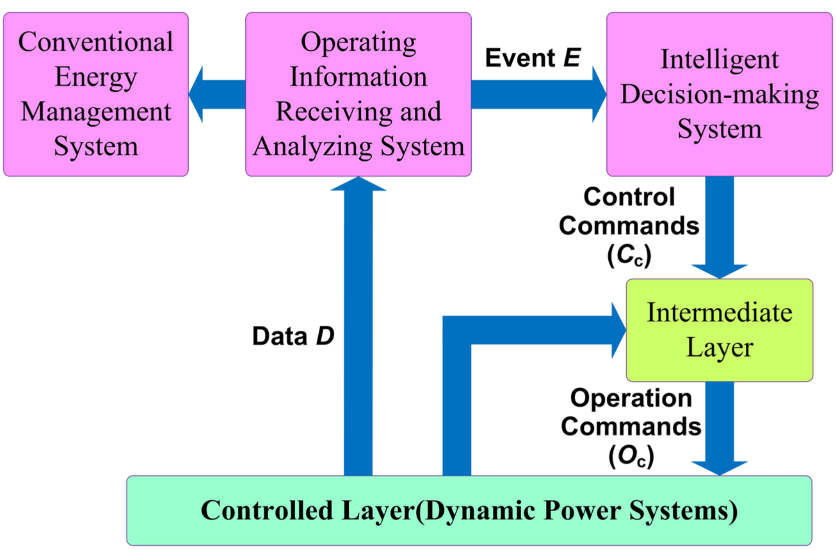

FIGURE 13 The architecture of the hybrid control system for the smart grid in China which put more emphasis on the dispatching network distinctly. Here, such hybrid control theoretical framework is the basis for the operation of Smart-WAR that was first proposed by Prof Lu in 2011 [Colour figure can be viewed at wileyonlinelibrary.com]

Internet energy hub and multienergy flow model of microgrids,[80,81] which further enriches the mathematical models of multienergy coupling system and lays a firm foundation for the computation of multienergy flow and optimal dispatching of EEPS.

The above-mentioned multienergy coupling and complementary systems are better than the traditional power systems in terms of distribution, diversity, and randomness; thus, traditional centralized dispatching and control modes are facing considerable challenges from the increasingly complex cyber-physical-social EI systems with high penetration of renewables. A consensus is gradually formed in such a way that the framework of future EMS with multienergy flow is bound to be decentralized autonomy and centralized coordination (or collaboration).[74,82,83]

Taking the aforementioned Smart-WAR as an example, such concept was first proposed by Prof Lu et al in 2011 and can be seen as a specific example of the dispatching robot proposed at the first time in China. In their vision, they expect to build the entire power grid into a single Smart-WAR that has the operating capability to approach multi-index optimization automatically, thereby achieving the most advanced intelligent form that the grid can achieve. The theoretical basis for the operation of this form is the hybrid control system theory for power system (see Figure 13). The aim of Smart-WAR is to control the entire power system as like as an intelligent robot. Lu et al[70] pointed out that to implement Smart-WAR, there is still a need for major technological breakthroughs in basic measurement facilities of the smart grid, new state estimation system, standardized modeling and interfaces, power system operation evaluation index system, and the integration of machine intelligence and AI. Moreover, as a large number of distributed new energy systems are connected to the grid, it will bring the following two major challenges to the energy generation, transmission, transformation, distribution, consumption, and dispatching of the EI.

First, the explosive growth of data volume poses a huge challenge to the collection, storage, processing, and knowledge extraction of multisource, heterogeneous, high-dimensional, distributed, and nondeterministic data and flow data, making the data samples of the EI extremely complex and diverse; thus, a single Smart-WAR may not be able to address such massive sample datasets.

Second, high-penetration renewables will bring a challenge to the energy management systems of the EI. This is because energy networks such as power grids, natural gas networks, and heating (cooling) networks are increasingly tightly coupled and interconnected, which results in a gradual transition from simple power system energy management to multienergy coupled integrated energy management system of EI. Obviously, compared with traditional power systems, the multienergy coupled EI has stronger dispersion, diversity, and randomness. Therefore, the traditional centralized control model in Smart-WAR will face more challenges, and the future of multienergy flow energy management system architecture must be decentralized autonomy and centralized coordination. This also means that relying solely on a Smart-WAR will be difficult to support the safe, self-healing, green, strong, and reliable operation of the power grid in the EI.

On the whole, the proposed PDR conception in this paper is fundamentally different from the single Smart-WAR concept proposed by Lu et al.[18] A comprehensive comparison between the two is provided from seven aspects, including application-oriented field, core ideology, theoretical basis for operation, system framework, other key technologies needed, social factors consideration, and number of individuals in the system, as demonstrated in Table 2.

Therefore, although the good vision of Smart-WAR has been proposed, we deem that a single Smart-WAR will be unable to complete the increasingly complex and diverse dispatching and control tasks, and its working mode will inevitably be replaced by a mode in which multiple PDRs work collaboratively; thus, that is the idea of smart dispatching proposed in this paper from the perspective of parallel dispatch, called parallel dispatch or PDR, which will be elaborated in the following subsection.

4.3 | The conception of parallel dispatch

In this paper, we attempt to propose the concept of parallel dispatch, as a category of smart dispatching, which has been introduced into the complex cyber-physical-social EI systems. Taking the EEPS as a representative of the EI, we have depicted the application of parallel dispatch-based PDR or robots in the field of EEPS, involving the parallel dispatch framework and its KA techniques, including parallel system theory, PML, and group intelligence. The aim of PDR is to achieve smart dispatching under the condition of plug-and-play of smart energy in the power systems. Moreover, through multiple collaborative robots in a PML manner, we expect to achieve the highest level of intelligence form that can be achieved in the integrated EMS.

We deem that the EEPS containing a single PDR can be treated as a highly intelligent CPS, while the framework of the complex dynamic EI containing multiple interactive PDRs can be designed as a CPSS, as illustrated in Figure 14. In this framework of CPSS, the ability of

TABLE 2 A comprehensive comparison between the PDR conception proposed in this paper and the single Smart-WAR concept

	Conceptions	
Items	**Smart-WAR**	**PDR**
Application-oriented field	Smart grids in China	Cyber-physical-social EI systems, especially with the new generation of EEPS as a typical representative
Core ideology	Build the smart grid into a power grid with the operating ability to approach multi-index optimization automatically, and should meet the challenges of smart grid in the nearest future. Overall, its purpose is to control the entire power system as same as an intelligent wide-area robot, which is considered as the highest form of smart grid.	Based on the KA processes and PML methods in the centralized/decentralized dispatching modes of the future EEPS, its purpose is to realize the knowledge self-exploration by group PDRs and the automatic improvement of the group intelligence levels. Overall, based on decentralized autonomy and centralized coordination of PDR(s), its purpose is to effectively promote the dispatching level of EI by stimulating and utilizing the emerged knowledge in the system, and ultimately to achieve parallel dispatching and coordinated control in the EI under energy, information and society deeply integrated.
Theoretical basis for operation	Hybrid control theory for power system	The key theories of Energy 5.0, including KA theory, ML theory, parallel system theory, artificial society modeling theory, complex network theory, game theory, graph theory
System framework	Power hybrid automatic control system framework	Cyber-physical-social EI parallel dispatch system framework
Other key technologies needed	✓ Supervisory control and data acquisition (SCADA) technology in smart grid ✓ New state estimation systems ✓ Standardized modeling and interface technology ✓ Power system operation evaluation index system ✓ Combination of machine intelligence and human intelligence	✓ AI technologies, especially PML and DRL ✓ Complex system and artificial society modeling technology ✓ CPSS and CPS technology ✓ High performance computing and intelligent control technology ✓ Big data smart management and cloud computing technology ✓ Complex social computing technology ✓ Parallel control and management technology ✓ Multiagent modeling technology
Social factors consideration	Has considered the daily dispatching behavior of dispatching operators, and the hybrid control theory for power system on which it relies on is event driven as the core.	Has fully considered the complex social factors such as dispatchers, energy market, and users based on virtual-real interactions, which are realized via simulating human dispatcher groups with PDRs in the constructed VPAS.
Number of individuals in the system	Single Smart-WAR	Numerous PDRs

PDRs to make intelligent decisions can be effectively improved via the use of the PML method and intelligent decision-making module (ie, the KA module) in the virtual parallel systems by a considerable number of PDRs.

It is foreseeable that smart dispatching will be the one of the core techniques in the complex cyber-physical-social EI, and the parallel dispatch-based PDR will epitomize the high intelligence of the EI dispatching and control.

5 | PARALLEL DISPATCH FRAMEWORK CONSTRUCTION

Heretofore, the theoretical framework of Energy 5.0 put forward by Wang et al[5] is mainly developed aiming at power generation plants. Currently, no system architectures of Energy 5.0 are proposed in the field of EI. Consequently, it is essential to fully investigate the future needs of multienergy complementary projects and

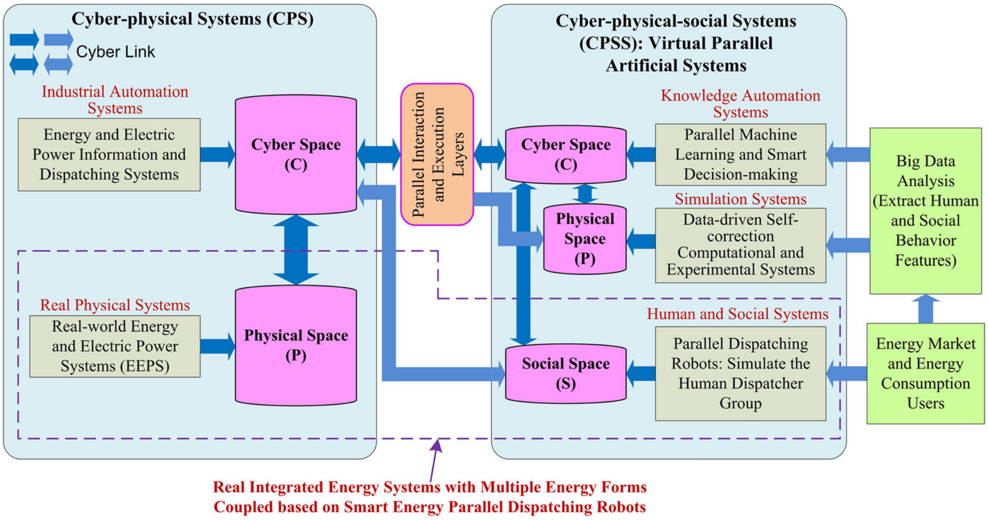

FIGURE 14 The parallel CPSS framework developed for the parallel dispatching of the multienergy coupled EI with a complex CPSS structure represented by new-generation EEPS. In this framework, the proposed smart PDRs are employed to simulate human dispatcher group considering human and social factors (eg, the energy markets) [Colour figure can be viewed at wileyonlinelibrary.com]

development trends of EI, through which, we should try to analyze the coupling models of human and social factors in the deep integration of physical systems, cyber systems, and social systems (ie, CPSS), as well as development trends and practical engineering demands of a new generation of EEPS (ie, EI), so as to build an ideal framework and an engineering feasible framework of the CPSS for EI.

For the multienergy system illustrated in Figure 7, it is very difficult to design an ideal framework of Energy 5.0 for this system, because such system owns very complex social elements, low cyber-physical integration, and insufficient information transparencies between different EMSs. For this reason, Qian et al[53] pointed out that the issues of Open Complex Giant Systems can be addressed through integrating the expert-group decision making and intelligent information tools. Therefore, the design of an engineering feasible framework of CPSS for the dispatching of EI (eg, the complex multienergy system demonstrated in Figure 7) should be conducted from the perspectives of complex system theory and parallel dispatch, which will be elaborated subsequently in the next subsection.

5.1 | Construction of an engineering feasible parallel dispatch framework

According to the ideologies of complex system theory and parallel dispatch, we develop a feasible parallel dispatch framework in engineering for the dispatching of EI represented by EEPS, and the overall control framework is demonstrated in Figure 15. Based on Figure 15, the internal details of this control framework are presented in Figure 16.

As shown in Figure 16, in this engineering feasible framework, we propose to adopt PDRs to replace the human dispatchers in the artificial system (ie, the cyber-space) from a perspective of parallel dispatch. Such replacement can effectively reduce the uncertainty of direct modeling of humans and societies. With a comprehensive consideration of the development trend of EEPS in China and the above-proposed two development forms of future CPS, as well as based on the idea elaborated by Deng et al,[5] we propose to use the framework of CPSS in Figure 14 to construct a control framework of parallel dispatch (as shown in Figures 15 and 16) for the optimal dispatching and control decision making of EI, so as to carry out related research work. This is in line with the actual needs of technological and economic development in China.

1) Three parts of the parallel dispatch framework

As demonstrated in Figure 16, the replacement of human dispatchers with PDRs is as like as AlphaGo; thus, in this parallel dispatch framework, we can also use MCTS method so solve the problem of a large amount of searching volume, the deep learning to solve the situation assessment problem, and the PML to solve the problem that the massive training samples are hard to obtain. Actually, the overall control system framework presented in Figure 15 is an extension of the traditional control systems, and it still includes three important parts as follows:

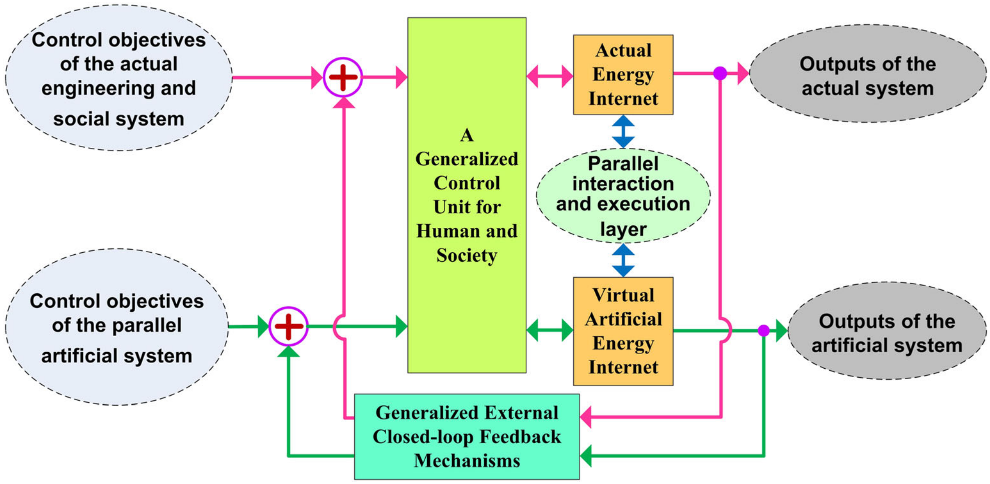

FIGURE 15 The overall control framework of parallel dispatch designed for the optimal dispatching and control decision making of EI [Colour figure can be viewed at wileyonlinelibrary.com]

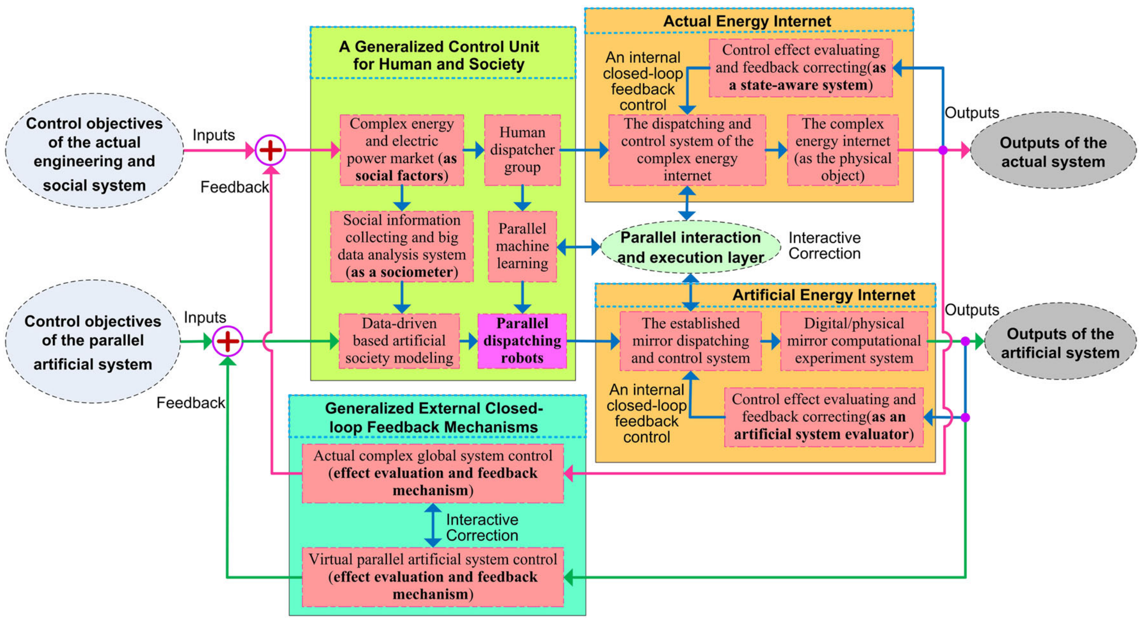

FIGURE 16 A more detailed control framework of parallel dispatch, in which an external global large closed loop and two internal small closed loops are designed, and group PDRs are used to replace human dispatchers [Colour figure can be viewed at wileyonlinelibrary.com]

i) The First Part: It is a generalized control module in the social space for the humans and societies. This part is constructed based on the comprehensive effects of human dispatcher groups and complex energy and electric power markets (ie, modeled as social factors). In this module, the social information collection and big data analysis system is regarded as a social sensor; the PML methods and data-driven–based artificial society modeling methods are applied into the group PDRs; the social factors collected by the social sensor are used for artificial society modeling; the social factors of the human dispatcher group are learned by the group PDRs via PML. This module finally outputs decisions of human dispatcher group and group PDRs to the physical space and cyberspace, respectively. This is performed by using PML to interact with physical and cyber spaces via parallel interaction and execution layer between physical space and cyberspace.

ii) The Second Part: It is composed of generalized controlled objects containing the original industrial closed-loop control systems (ie, the actual system) and the virtual parallel system (ie, the artificial system). The dispatching and control system of the EEPS, control effect evaluation and feedback correction module (ie, the state-aware system), and physical object of the EEPS are included in the actual system, and a small closed control loop is performed among them. The artificial system contains the mirrored dispatching and control system, digital/physical mirrored simulation system, and control effect evaluation and feedback correction module (ie, the artificial system evaluator), and similarly, a small closed control loop is performed among them. In addition, the mutual correction is conducted between the actual system and artificial system via the parallel interaction and execution layer. The actual outputs and simulation outputs are obtained from the physical object of the EEPS and the digital/physical mirrored simulation system, respectively. Overall, the physical space (ie, the physical system) is formed by the actual system and the cyberspace (ie, the cyber system) is formed by the artificial system, and they interact with each other via the parallel interaction and execution layer. Hence, the first part together with the second part forms a complete cyber-physical-social system, ie, a CPSS, in which the human and social factors are fully considered. The actual system and artificial system form a mode of virtual and real interaction and parallel execution. That is the core foundation of the idea of parallel dispatch. Certainly, in order to evaluate this parallel execution, we need to introduce some evaluation mechanisms, which form the third part in the control framework of parallel dispatch.

iii) The Third Part: It is an evaluator containing some generalized large closed-loop feedback mechanisms; thus, this part is also called a generalized large closed-loop feedback manager. The manager is composed of two modules: the first module performs control of the actual complex large system based on quality evaluation and feedback mechanisms, and the second module performs control of the virtual artificial system based on quality evaluation and feedback mechanisms. Therefore, on the whole, this manager is employed to evaluate the outputs (ie, the actual and simulation outputs) of the whole system (ie, the physical system and the parallel artificial system), including the causal variations of human and social attribute caused by control of the outputs. The actual outputs and simulation outputs, and the generalized large closed-loop feedback manager, together with the control targets of engineering-society systems and the control targets of artificial systems form an external large closed loop. Hence, this control framework of parallel dispatch contains three closed loops when counting in the two small closed control loops in the second part.

2) Two roles played by the parallel dispatch framework

Based on the designed closed loops, group PDRs in this control framework developed in Figure 16 are used to replace the human dispatcher group to form a mode of parallel dispatch, which can theoretically play two roles during actual parallel execution as follows:

On one hand, we can effectively address the most critical issue, ie, the modeling of human and social behaviors, via the above-proposed replacement. Moreover, at this point, the decision-making capability of PDR is only limited due to the data space and learning ability possessed by the PDR, instead of natural biology attributes such as emotion and fatigue. Hence, the advantages of VPAS could be fully taken in aspect of guiding the real physical system.

On the other hand, we can achieve that group PDRs learn from the real human dispatchers through VPAS and PML methods. This is similar to the idea of AlphaGo who can improve its decision-making capability via continuously playing with real human Go players and learning from human history records,[46] and even via tens of millions of self-play games without human knowledge.[47,48] Therefore, the group PDRs in this control framework of parallel dispatch can continuously improve their intelligences based on learning by self-exploration, ie, the continuous interactions between actual systems and virtual artificial systems, called virtual and real interaction.

3) Significance of this control framework

This control framework is constructed based on the idea of parallel dispatch, in which the smart grid is taken as the core and the information flow and energy flow in the EI are taken as the links, and supported by the big data and AI techniques such as DRL and PML algorithms[65], such that it is possible to build an intelligent control and PDR for the smart grid to achieve unmanned EEPS.

In this control framework of parallel dispatch, the idea of parallel system is to establish one or more artificial virtual systems with certain purposes (eg, planning, control, and management) corresponding to the actual system. Through the learning and optimization of the artificial virtual system, thereby achieving interactions with the actual system, and ultimately achieve control and management of complex real systems.

Like AlphaGo, theoretically, the intelligences of these PDRs in the control framework will reach to or eventually surpass that of human dispatchers, which is deemed to be crucial to the engineering implementation of group PDRs in practice.

Inspired from AlphaGo, we expect to build the parallel EI based on the theories of parallel system in the future. Further, on the basis of the Internet (ie, data and information interconnection), the Internet of things (ie, sensing and control interconnection), and the EI (ie, the interconnection of energy elements), we expect to build a cyber-physical-social energy network with knowledge and intelligence interconnection, ie, the Internet of Minds (IoM)-based energy system.

5.2 | Design of an experimental platform based on the parallel dispatch framework for PDR research

The design of an experimental platform based on the control framework of parallel dispatch can be conducted in three procedures as follows.

First, we need to build a parallel artificial system containing a nominal model and a mirrored model based on the existing integrated parallel computation and simulation platform for smart grid, which has been developed based on Java Agent Development Framework (ie, JADE, an agent development framework based on Java language), Matlab, and GAMS (ie, general algebraic modeling system).

Second, we need to investigate the mirrored model and parametric correction method based on system identification techniques, and the digital simulation system of EEPS with online self-correction ability based on big data technique and the framework PML, thus achieving self-exploration of the mirrored simulator for better operation modes and control effects, and meanwhile possessing the ability to guide the real physical system to approach the ideal optimal state simulated by the simulation system.

Lastly, based on the established modes and platform, and these investigations, an experimental platform suitable for subsequent theoretical research on CPSS could be built based on the control framework of parallel dispatch as presented in Figures 15 and 16.

Overall, the above construction procedures include two parts: theoretical research and system development. Obviously, the two should be carried out simultaneously with a mutual promotion. Therefore, the focus at this time is to build an experimental laboratory environment for basic theoretical research, and then, after the theoretical research is mature, finally complete this experimental platform constructed based on the physical systems and mirrored models. The concrete contents for the construction of this experimental platform are introduced as follows.

a. Build the experimental research platform

The experimental research platform of parallel system simulator containing a nominal model and a mirrored model, as stated preciously, is built based on the existing digital simulation system of the EEPS, as demonstrated in Figure 17. The design of this framework of experimental research platform for parallel CPSS in Figure 17 is implemented via three steps as follows:

Step 1: Based on the existing integrated parallel computation and simulation platform for smart grid, we use the simulator of the normal model consisting of standard parameters to replace the real physical system (ie, the physical system of the EEPS), which is as shown in the lower right section of Figure 17.

Step 2: We then adopt the simulation model such as a reduced-order load model and a power supply model developed with certain parameter errors and dimensionality reduction to replace the above-mentioned mirrored model on the premise of ensuring that the power flow of the system is consistent and the system dynamic swing characteristics are similar, which is as shown in the lower left section of Figure 17.

Step 3: According to the multiagent framework adopted in the JADE, we implement parallel arrangement and distributed modeling using the nominal model and the mirrored simulation system. Based on the three steps stated above, we can finally construct the framework of an experimental research platform for the research on parallel dispatching of the EEPS.

The aim of this paper is to investigate the smart dispatching of the EI represented by the EEPS from the perspective of parallel dispatch, and the corresponding KA technologies of the PDR. Thereby, it should be emphasized that the research object in this paper is PDR group; thus, both the nominal model and mirrored model must be a distributed modeling and simulation system that owns parallel computation capability. This is essentially different from the well-known power system simulation software platforms such as Bonneville Power Administration (BPA) software and Power System Analysis Software Package (PSASP), which adopt the centralized modeling and centralized offline simulation methods. Therefore, we should focus on the development of such distributed modeling and simulation system, which will lay a firm foundation for the development of PDRs in the future.

b. Distributed modeling and simulation system

This distributed modeling and simulation system is reflected in the multiagent JADE-, Matlab-, and GAMS-

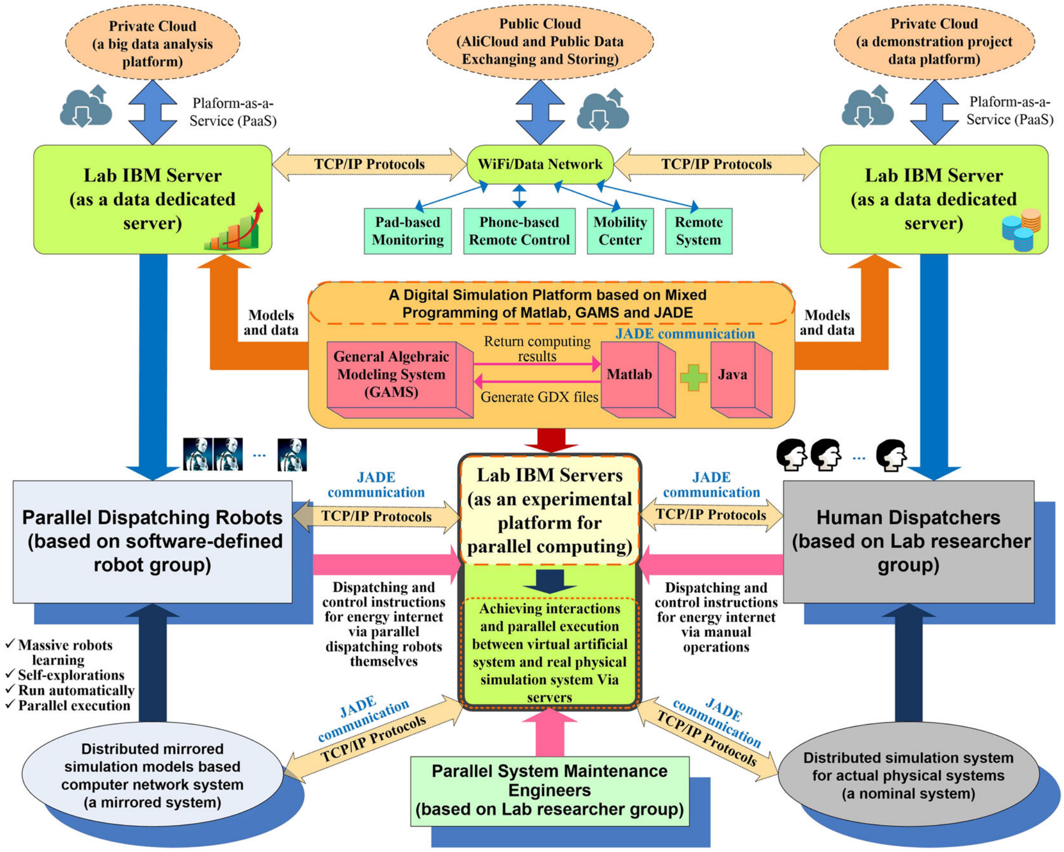

FIGURE 17 The framework of an experimental platform designed for future study of PDR [Colour figure can be viewed at wileyonlinelibrary.com]

based integrated parallel computation and simulation platform for smart grid, as demonstrated in Figure 17. In fact, this platform has been preliminarily used by us in some scenarios, such as the optimal dispatching analysis of AC/DC hybrid main power grid in CSPG, the dynamic analysis of the automatic generation control systems in CSPG, and the system-wide simulation of united control for a complex microgrid built by us containing wind power, photovoltaic, thermal power, and hydropower networks.

This parallel computation and simulation platform is developed based on JADE, Matlab, and GAMS. On the one hand, the adoption of JADE is because JADE is a multiagent system platform developed based on Java language and conforming to the FIPA (ie, The Foundation for Intelligent Physical Agents) specifications, such that the clock synchronization characteristic of the real physical systems and mirrored simulation systems can be ensured during the process of digital simulation, and the real-time parallel interaction of the data for them is also guaranteed simultaneously. In fact, the multiagent system is also recommended by Wang et al[10,11,15] as a construction scheme of parallel system. Therefore, the multiagent system developed based on JADE is very suitable for the construction of the parallel dispatch framework used in the complex cyber-physical-social EI system. On the other hand, the use of hybrid modeling and programming techniques based on Matlab and GAMS is achieve the third-party custom modeling and optimal power flow calculation for the multienergy coupling and complementary system networks. Concretely speaking, the GAMS as an advanced modeling system with powerful mathematical programming and optimization capabilities can be used for large-scale node networks modeling and solving of the optimal power flow of the multienergy flow model at the bottom of the EI. The Matlab as a commercial mathematics software produced by MathWorks in the United States is a high-level technical computing language and interactive environment for algorithm development, data visualization, data analysis, and numerical calculation, including two parts: Matlab and Simulink. Therefore, the Matlab in this platform is employed to implement intelligent ML algorithms (eg, PML) programming and complex components modeling via the M language.

c. Multienergy coupling and complementary system research foundations

The above-introduced JADE-Matlab-GAMS–based integrated parallel computation and simulation platform for smart grid (see Figure 17) can be extended to apply in the field of multienergy coupling and complementary systems. For instance, we have preliminarily employed this platform in a typical three-region 33-node energy center testing system for optimal power flow analysis, including centralized dispatching analysis and multiregion decentralized dispatching analysis. This testing system contains several subregions, and each of them contains a 14-node power network, a 20-node natural gas network, and 11 energy centers. The typical framework of this energy center is depicted in Figure 18A, and its corresponding network topology structure is presented in Figure 18B.

In the future, we expect to further expand the scale of simulation nodes of this energy center testing system and make it being a large-scale EEPS consisting of 5000 grid nodes, 5000 natural gas network nodes, and 500 energy centers for the optimal power flow analysis. In such large-scale testing system, the simulation requirements for the dispatching issues research in the parallel CPSS framework based EEPS can be fully satisfied.

d. Parameter self-correction method research for the mirrored model

The parameter self-correction method for the mirrored model should be investigated in the above-introduced computing experimental environment (in which model customization is possible) of the parallel dispatching system. However, we deem that it still requires in-depth research and secondary development work on how to conduct online self-correction in parallel operation of the system. Therefore, based on the parallel dispatching system and combined with the existing system identification methods, we should further develop a new self-correction digital computing experimental system for the EEPS based on the big data technique and the framework of PML, such that we can achieve self-exploration of better operation modes and control effects via the mirrored computational experiments, and can possess the capability of guiding real

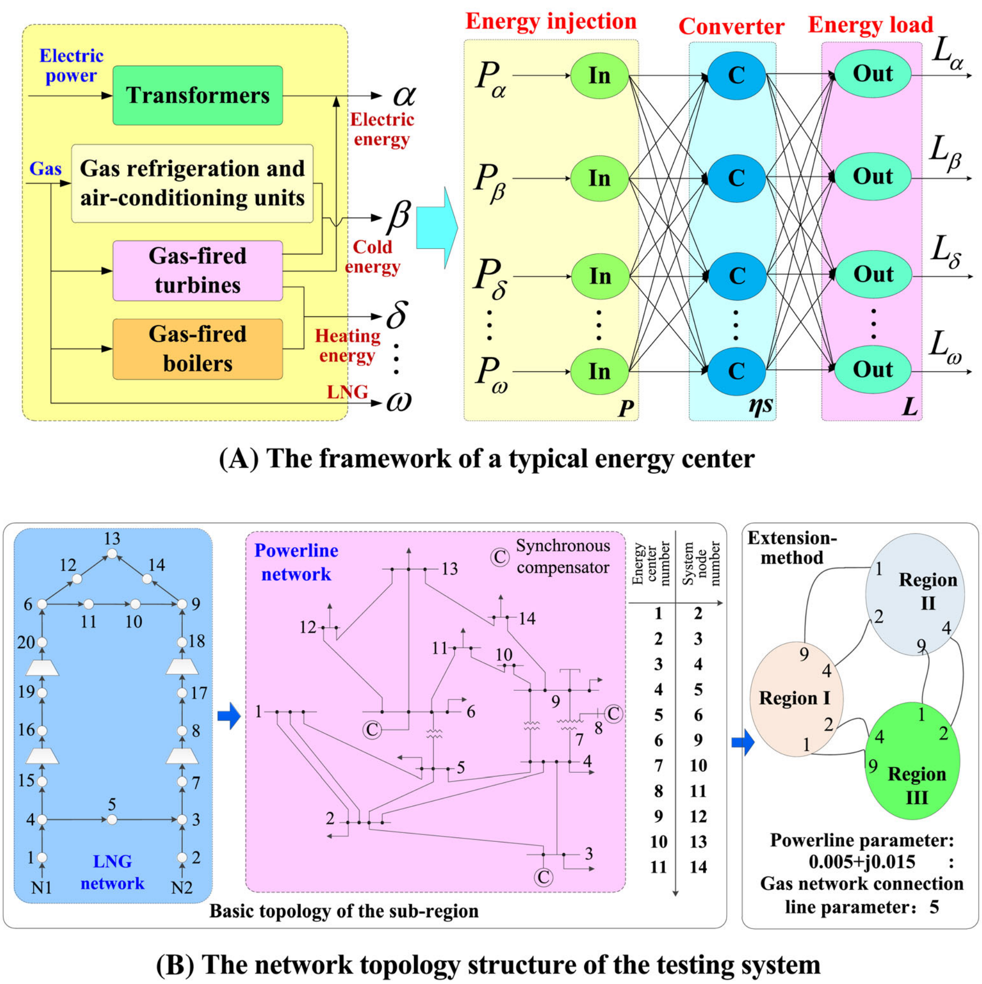

FIGURE 18 Illustration of a regional integrated energy testing system, where (A) shows the structure of the three-zone 33-node energy center testing system and (B) gives the structure of a typical energy center [Colour figure can be viewed at wileyonlinelibrary.com]

physical systems to approach an ideal optimal state that is simulated by the mirrored computational experimental system (ie, the self-optimizing ability). Finally, based on the investigations introduced above in this section and the parallel dispatch framework, we can construct an experimental platform (see Figure 17) for subsequent theoretical research on PDR.

6 | IMPLEMENTATIONS ON PML-BASED SAS MODELING FOR THE PROPOSED PDR

Generally, hierarchical centralized dispatching modes are mostly adopted in traditional power systems. In such dispatching modes, dispatching information and tasks are aggregated and released through a centralized control center as presented in Figure 19. For example, the major dispatching mode adopted in a small-scale integrated EEPS is still centralized with centralized energy management system (EMS) architecture (see Figure 19). However, such centralized dispatching mode cannot be used in a large-scale EI system with multiple coupled and complementary energy forms due to four reasons as follows. First, with the increase of the system scale, the number of controllable variables is also increasing and this easily leads to the phenomenon of the curse of dimensionality in the system. Second, the information flow is highly integrated with the energy flow to form a bidirectional circulation, which causes the amount of information collected to rise sharply, and results in communication and information processing bottlenecks. Third, the centralized EMS has lower reliability, so when it fails, the controllable equipment in the grid cannot be optimized to operate autonomously. Lastly, due to privacy, the use of centralized optimization algorithms does not necessarily capture global information (ie, the global optimum), which results in algorithm failure.

Therefore, based on the investigations conducted in Sections 2 to 5, we attempt to investigate how to implement SAS modeling based on ML methods for the PDRs in the EI with a CPSS structure. In this section, we first investigate the modeling of a typical energy dispatching center, and based on which, we then investigate the methods of SAS modeling in the centralized and decentralized dispatching modes respectively. Concretely speaking, the investigations in this section can be carried out in four steps as follows. First, we study the dispatching tasks with different time scales and multiple optimization objectives and their requirements for real-time control in a single regional integrated energy dispatching center (which is illustrated in Figure 19). Second, based on the existing optimal dispatching models and intelligent algorithms used for the multienergy flow systems, we further investigate the advanced ML methods suitable for SAS modeling, which are combined with deep RL algorithms. Third, we investigate the method generating massive training data samples for PML via the virtual and real interactions based self-exploration method, ie, the interactions between mirrored simulation system (ie, the software-defined system) and real physical system (ie, the physically defined system), as demonstrated in Figure 20. Lastly, based on the investigations in precious three steps, we further investigate the KA

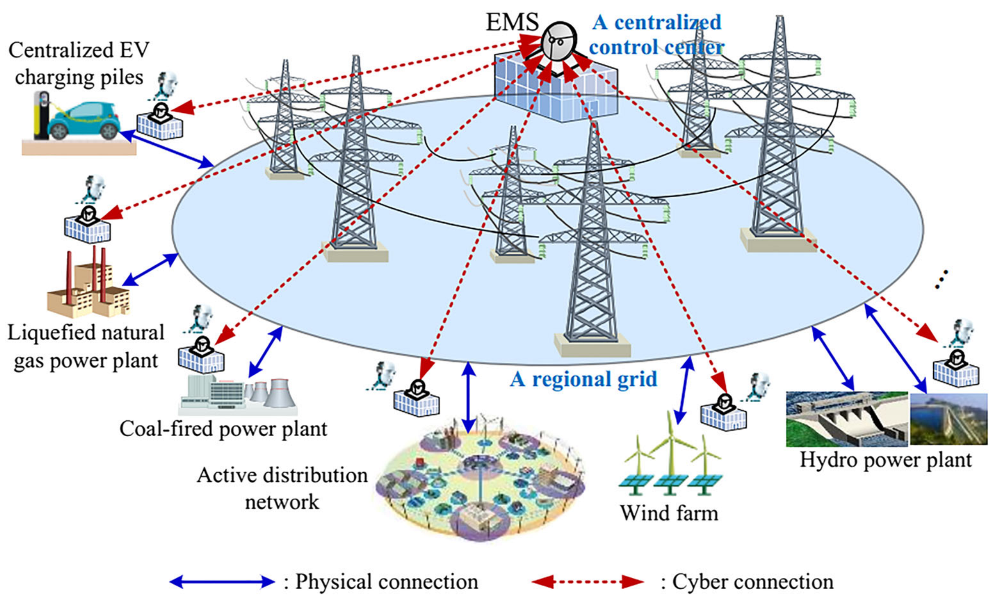

FIGURE 19 Illustration of a conventional centralized EMS framework of a centralized control center [Colour figure can be viewed at wileyonlinelibrary.com]

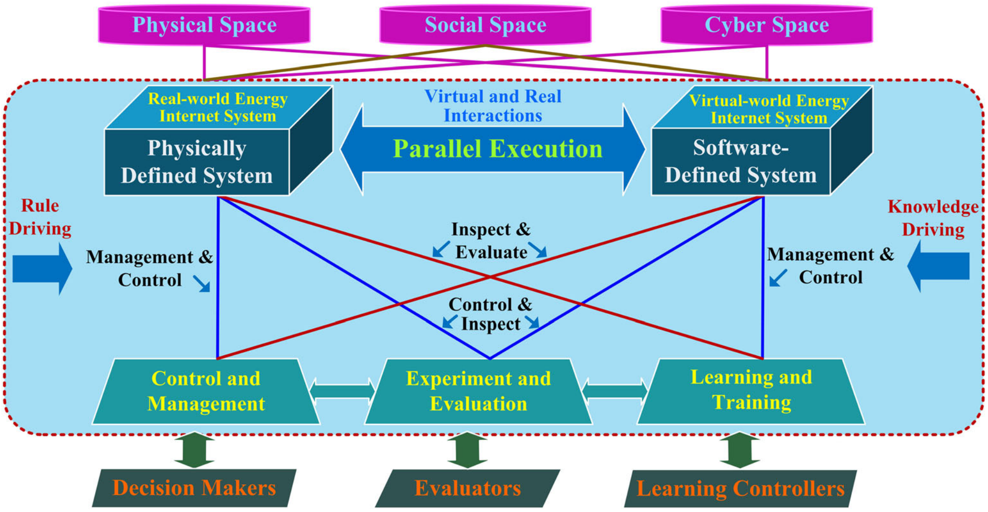

FIGURE 20 The parallel control framework for virtual-real interactive complex system control and management [Colour figure can be viewed at wileyonlinelibrary.com]

processes and PML methods of a single PDR in the centralized dispatching modes and group PDRs in the decentralized dispatching modes.

6.1 | Modeling of a single regional integrated energy dispatching center

In this subsection, we focus on the modeling approach of a single regional integrated energy dispatching center as illustrated in Figure 19, ie, the dispatching tasks with different time scales and multiple dispatching objectives and their requirements for real-time control in a single regional integrated energy dispatching center. In such dispatching center, three different categories of dispatching tasks are integrated with different time scales, ie, power system dispatching tasks, natural gas dispatching tasks, and combined heat and power (CHP) dispatching tasks. Therefore, multiple coupled and complementary forms of energy dispatching tasks are involved in this single regional dispatching center with different time scales. This center is a typical centralized dispatching and control center, as demonstrated in Figure 19.

In Figure 19, we assume that the energy forms involved in this regional dispatching center are α, β, $\cdots$, ω; correspondingly, then the energy injections are denoted as P_α, P_β, $\cdots$, P_ω, and the energy loads are represented as L_α, L_β, $\cdots$, L_ω, respectively. Thereby, the power conversion equation of this single regional centralized energy dispatching center can be expressed as

$$\boldsymbol{L} = \boldsymbol{\eta}\boldsymbol{s}\boldsymbol{P}, \tag{1}$$

where $\boldsymbol{L}$ is the energy load vector. $\boldsymbol{\eta}$ is the efficiency matrix of conversion devices. $\boldsymbol{s}$ is the coupling coefficient matrix, which physically means the proportion that various energy resources get through different converters. $\boldsymbol{P}$ is the energy injection matrix (or vector). Note that it is not a source injection, but a power flow injection of various energy resources. If we only consider the coupling relationship between power grid network and natural gas network, and then the power conversion equation in (1) is simplified as

$$\begin{cases} L_{\mathrm{e}} = \eta_{\mathrm{trans}}^{\mathrm{e}} P_{\mathrm{e}} + \eta_{\mathrm{CHP}}^{\mathrm{e}} v_{\mathrm{ge}} P_{\mathrm{g}}, \\ L_{\mathrm{h}} = \eta_{\mathrm{CHP}}^{\mathrm{h}} v_{\mathrm{ge}} P_{\mathrm{g}} + \eta_{\mathrm{Fur}} v_{\mathrm{gh}} P_{\mathrm{g}}, \\ L_{\mathrm{g}} = (1 - v_{\mathrm{ge}} - v_{\mathrm{gh}}) P_{\mathrm{g}}, \end{cases} \tag{2}$$

where L_{e}, L_{h}, and L_{g} are electric power load, heat load, and natural gas load, respectively. P_{e} and P_{g} are electric injection power and natural gas injection power, respectively. v_{ge} and v_{gh} are the ratios of natural gas gets through the gas turbine and gas-fired boiler, respectively. $\eta_{\mathrm{trans}}^{\mathrm{e}}$ is the transformer efficiency. $\eta_{\mathrm{CHP}}^{\mathrm{e}}$ and $\eta_{\mathrm{CHP}}^{\mathrm{h}}$ are the generating efficiency and the thermal efficiency of gas turbine, respectively. η_{Fur} is the thermal efficiency of gas-fired boiler.

Similar to the issues of power system multiobjective optimal dispatching issue, the multiobjective optimal dispatching issues of an integrated energy system in a centralized control center can also be solved. For example, on the premise of satisfying system security constraints and load demands, the targets aiming at achieving an optimal state via adjusting controllable variables (eg, coupling coefficients, and the output of various energy forms) in a reasonable way can be modeled as

$$\begin{cases} \min \quad W \\ \text{s.t.} \begin{cases} \boldsymbol{L} = \boldsymbol{\eta}\boldsymbol{s}\boldsymbol{P} \\ \boldsymbol{G}(\boldsymbol{P}_{\mathrm{in}}, \boldsymbol{P}, \boldsymbol{L}, \boldsymbol{\eta}, \boldsymbol{s}, \boldsymbol{f}, \boldsymbol{v}) \le 0 \\ \boldsymbol{H}(\boldsymbol{P}_{\mathrm{in}}, \boldsymbol{P}, \boldsymbol{L}, \boldsymbol{\eta}, \boldsymbol{s}, \boldsymbol{f}, \boldsymbol{v}) = 0 \end{cases} \end{cases}, \tag{3}$$

where W is the optimization objective, including a functional cost objective W_e and a carbon emission objective W_c. $\boldsymbol{P}_{\mathbf{in}}$ is the source injection matrix. $\boldsymbol{f}$ is the branch power matrix. $\boldsymbol{v}$ is the node state matrix. The first line of the constraints is the conversion relationship of the energy center (ie, the coupling constraints of various energy forms), and the second constraint $\boldsymbol{G}$ and the third constraint $\boldsymbol{H}$ are the system inequality and equality constraint sets, respectively.

Therefore, similar to traditional power systems, the dispatching and control tasks of a new generation of EEPS can still be divided into different time scales, including day-ahead unit commitment, day-ahead 96-node generation dispatching, ultra-short-term real-time dispatching within 15 minutes and AGC (ie, automatic generation control) within 1 minute. However, the time scales of electric power, gas, heating, and cooling networks vary considerably. How to select a reasonable time scale to classify their joint centralized dispatching tasks in future is a crucial issue. To this end, it is necessary to conduct a comprehensive research on different energy flows in terms of their dynamics change process and characteristics, difference of response characteristics on time scales, and behavioral responses to dispatching instructions, and so on. For example, a research can be carried out on mixed time-scale-based optimal dispatching of multienergy flow systems.[74] Such research is crucial to the investigations conducted in following sections on the PML-based optimal dispatching issues of cyber-physical-social EI system with different time scales.

6.2 | ML methods used in SAS modeling

In recent years, some conceptions and ideas of smart dispatching of power systems have been continuously raised. Among these, the power grid dispatching and control center of China Southern Power Grid (CSPG) has been implementing the idea of Dispatching Cockpit.[84] Under this background, each subordinate power grid dispatching and control center of the provincial grid corporation in CSPG has carried out a lot of work on realizing the automation of dispatching and control processes in smart grids,[85] such that the situation of manual intervention in the EMS by human dispatchers is becoming rare. Such research work is also the engineering feasibility basis of the Smart-WAR concept, which has been elaborated in previous sections and was first proposed by Prof. Q. Lu, an academician of the Chinese Academy of Sciences, in 2011.[18]

Generally speaking, for the feasible logic modeling of most of the dispatching processes and principles in above-mentioned research work, we can easily use heuristic rules (ie, *if … then …*) to achieve knowledge representation. However, for the modeling of dispatching processes and principles in the field of EI, a large amount of complicated abstract knowledge require more advanced knowledge extraction and storage methods to achieve knowledge representation. For this reason, we need to investigate how to implement the KA of centralized dispatching and control processes by a single PDR in the EI system, as well as investigate the advanced ML methods such as deep reinforcement learning (DRL) based on existing optimal dispatching models and smart algorithms used in a multienergy flow system.

Actually, as elaborated in Section 3, we have made some attempts to employ the Q-matrix used in reinforcement learning (RL) algorithms (eg, Q-learning algorithm) to a Markov decision process (MDP) over the past few years, with the aim of achieving value function storage in an intermediate process of optimization and decision making.[78] In this aspect, we have achieved a satisfactory effect in optimization acceleration. Therefore, we can use existing integrated energy centers (eg, the conventional centralized energy dispatching and control center as illustrated in Figure 19) to complete advanced knowledge extraction and representation during the process of joint dispatching and controlling of power networks, liquefied natural gas (LNG) networks, CHP networks. Inspired by this, based on existing optimal dispatching models and intelligent algorithms of multienergy flow system, we can carry out the possible research directions on advanced ML algorithms such as DRL methods, including the following: (a) We can combine the deep learning (DL) methods with the Q-learning to form some new deep Q-learning (DQL) algorithms; and (b) we can combine the DL methods with the ADP method to form some novel deep ADP (DADP) algorithms. Among these, one of the DADP algorithms is developed as presented in Figure 21.

Actually, the ADP algorithm mentioned above is also recommended as a core component in parallel system design,[10] such as a parallel ADP algorithm. Therefore, based on the DADP demonstrated in Figure 21, we propose to integrate three different time scales of dispatching and control issues in the parallel dispatching of the EI systems, ie, 15-minute economic dispatching (as tertiary frequency regulation), AGC (as secondary load-frequency control), and optimal assignment of generation control instructions, into a powerful intelligent algorithm library, such that a novel integration algorithm could be developed. In addition, we have assumed multiple kinds of simulation experiments for the islanded microgrid, including normal situation, plug-and-play start and stop situation, communication failure situation, all-day disturbance situation, time-varying topology situation, and

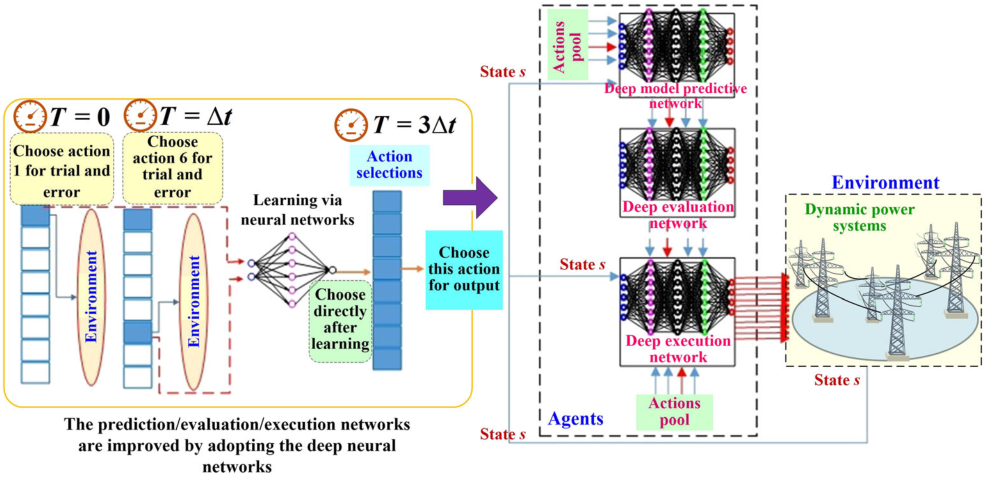

FIGURE 21 The architecture of a novel DADP algorithm [Colour figure can be viewed at wileyonlinelibrary.com]

mass simulation training samples based systemic internal parameters varying situation. The duration of all these simulations is configured as long as 25 years. Through the simulation and comparison with multiple optimization and control integrated algorithms, the feasibility, effectiveness, and robustness of the proposed DADP algorithm can be verified.[86] This can be seen as an important foundation for implementation of smart dispatching of the complex cyber-physical-social EI from the perspective of parallel dispatch. In this way, in addition to the above-mentioned ML methods used in SAS modeling for smart dispatching, we also need to investigate how to use the virtual and real interaction between the mirrored simulation system and real physical system to generate massive training data samples in a self-exploration manner, thereby achieving advanced PML for the PDR. This will be elaborated in next section.

6.3 | A PML method to generate massive training datasets for PDR

In the course of ML research over the past few years, we always have to face some very challenging issues in ML, and the biggest one is how to obtain the most valuable data samples for machines' learning with the minimum costs. For instance, when the research object is complex high-dimensional systems, although the aforementioned RL or DRL methods are capable of guaranteeing the validity of learning within a certain range, they cannot be well applied to the non-Markov decision processes. In addition, although the RL methods can be employed to realize online learning via active explorations, the extremely high dimensions of the system state generally make it difficult to explore feasible solutions when facing complex data processing, called the curse of dimensionality.

Therefore, in this section, we deem that it is essential to investigate a new self-exploratory approach (ie, advanced ML methods) to generate massive training data samples for PDR via interactions between the virtual world and real world, ie, the virtual mirrored system and real physical system (see Figure 20). Fortunately, a novel approach may be adopted for the PDR to address this issue, which is inspired by the AlphaGo and the theoretical framework of PML.

The biggest highlight for ML of the PDRs lies in adopting the latest theoretical framework of parallel learning proposed by Wang et al,[60,61] as demonstrated in Figure 22. In previous sections, we have elaborated that based on PML and parallel system theory, the parallel CPSS can be used to generate large amount of effective data samples to improve the ML capability of the PDR. Therefore, it is necessary to investigate the PML methods in depth for parallel dispatching of the cyber-physical-social EI system in a new theoretical framework of ML.

As stated in Section 3, the new theoretical framework of PML has been extended to three stages, ie, the data processing stage (Stage I), the action learning stage (Stage II), and the data/action interactive enhancement stage (Stage III). Among these, stage I is a process of generating big datasets via the artificial system for updating the ML models, including synthetic data and specific raw small data; stage II is a process of depicting the dynamic variations of the system states based on the idea of RL, but what is special is that the computational experiments are used to implement predictive learning in the process of parallel learning; and stage III is essentially a process of retaining and eliminating some big datasets, which is used to effectively deal with possible variations occurred in the original datasets.

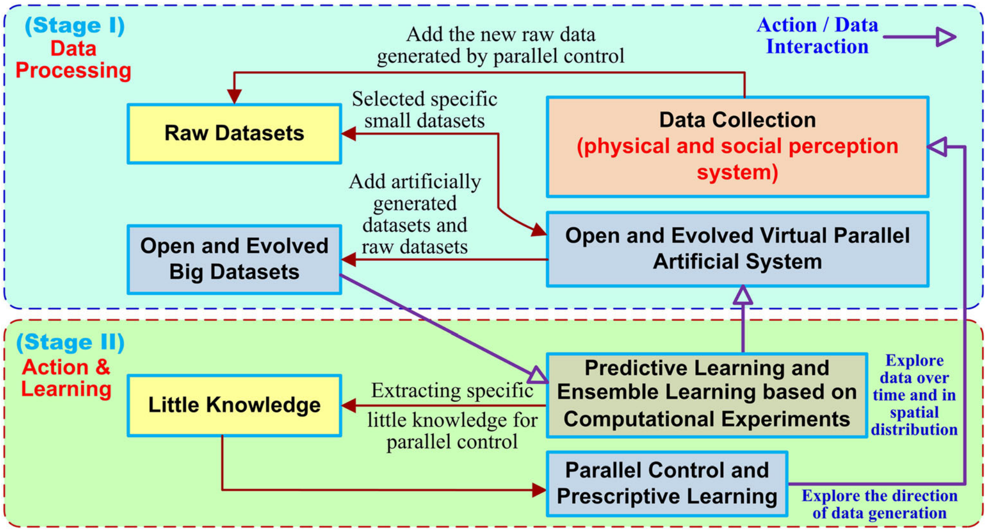

FIGURE 22 The theoretical framework of parallel machine learning (ie, PML), in which two stages of PML are demonstrated [Colour figure can be viewed at wileyonlinelibrary.com]

6.4 | SAS modeling of a single PDR in centralized dispatching modes

The above-mentioned three stages included in the theoretical framework of PML are very suitable for the SAS modeling of a single PDR in the centralized dispatching modes. According to these three stages, we can use the predictive learning, ensemble learning, and prescriptive learning to extend classical ML approaches, such that we can develop advanced ML methods for a single PDR in centralized dispatching modes. Here, as demonstrated in Figure 22, the predictive learning is used to how to explore data over time, the ensemble learning is used to solve how to explore data in spatial distribution, and the prescriptive learning is used to solve how to explore the direction of data generation.[60] To be more specific, three procedures to achieve advanced ML methods development by PDR are elaborated as follows.

First, we allow multiple PDRs to work collaboratively. At this point, each of them is treated as an agent that is able to continuously acquire some data samples via independent observations to form a dataset. In addition, each agent can also continuously take some actions independently to form an action set.

Second, we need to guarantee that the data obtained by each PDR is independent, as well as the number and timing of actions taken. Under this condition, we first allow an action can generate multiple new data samples, and then we require that the data acquisition and action completion must be performed successively at intervals when using the RL method, while the parallel learning is allowed to perform with different frequencies and orders of occurrence for obtaining data and completing actions.

Lastly, we observe the evolution of the system state from the perspective of parallel world (which has been elaborated in Section 3). From this, we can predict and analyze the results of expected actions through a large number of long-term simulation iterations when we map newly acquired datasets into the parallel space, and finally, we return the optimal actions back to the real space.

In the theoretical framework of PML (see Figure 22), the predictive learning is originated from the interpretation of cognitive psychology in children's learning style. We deem that the parallel system method based on computational experiments is the same as the predictive learning in essence. In short, the core of parallel system and predictive learning is to model the real environment with machines, so as to predict the likely future via simulations, and understand how the world operates through observations and demonstrations. During this process, the simulation is unsupervised or semi-supervised, while the initial state and final result are supervised. Such learning method is called parallel prediction plus perspective learning by Li et al,[61] which can be combined with three categories of learning manners, ie, unsupervised learning, semisupervised learning, and supervised learning, to fill the gap between various ML algorithms.[56]

Based on the above extensions for the PDR in the novel theoretical framework of PML, we can decouple the data and actions to a certain extent, which greatly expands the existing RL methods. This can be seen as the result of using a single PDR for medium- and long-term simulation iterations to predict and analyze the expected actions. Moreover, the processes of data generation and actions generation are relatively independent without time alignment. We deem that this is a typical process of shifting from actual small data to virtual big data. Actually, the above extensions have been reflected in the program of AlphaGo, who is seen as the epoch-making AI products. AlphaGo can be seen as an outstanding representative of a single robot. By using the latest PML framework (see Figure 22), we can greatly enhance the independent ML capabilities of a single PDR in a centralized dispatching manner.

The principle of parallel learning for a single PDR can also be visually explained by the data/action diagram of AlphaGo, as demonstrated in Section 3. Here, the parallel worlds are viewed as an integration of datasets and action sets, while multiple virtual parallel worlds are generated via the VPAS. For the parallel learning system of a single PDR, the data in the real world can be mapped to the parallel world (ie, the real existing operation states), which is generated by the VPAS, and then the multiline iteration manners can be taken to calculate various possibilities of the real world evolving to other parallel worlds, mathematically, ie, the possibilities of the current state transferring to other states. In this process, the decision making of each step can be evaluated by the RL algorithms (eg, ADP algorithm and Q-learning algorithm), such that the action with highest reward will be chosen for decision making. This is obviously a typical process of Markov decision making. In addition, the ensemble learning in Figure 22 is suitable for ML of group PDRs, including multiagent dispersed learning and collaborative learning mechanism, which will be discussed in detail later.

6.5 | SAS modeling of group PDRs in decentralized dispatching modes

As introduced preciously, the rapid development of smart grids has been promoting the development of EMS of power systems shifts from centralized dispatching and control to the form of decentralized autonomy and centralized coordination, which will be evolved into a series of small EMS families, including the thermal power station EMS, wind power station EMS, photovoltaic power station EMS, and hydropower station EMS on the source side, the power transmission network EMS (T-EMS), transformer substation EMS (S-EMS), power distribution network EMS (D-EMS) and microgrid network EMS (u-EMS) on the network side, and the electric vehicle clustering EMS (V-EMS), smart building clustering EMS (B-EMS) and household clustering EMS (H-EMS) on the load side,[82] as demonstrated graphically in Figure 23. As a result, the smart dispatching from a perspective of parallel dispatch for EI will inevitably be a group (ie, a series of small families), called group PDRs. The core investigations on them are KA process, SAS modeling, and PML of group PDRs, which will be highlighted in the following several parts.

1. KA process

As elaborated earlier, the KA means the automation of knowledge work, ie, the plug-and-play of hardware and KA of software design. In this part, KA here refers to the automation of knowledge work in the distributed dispatching and decentralized control processes

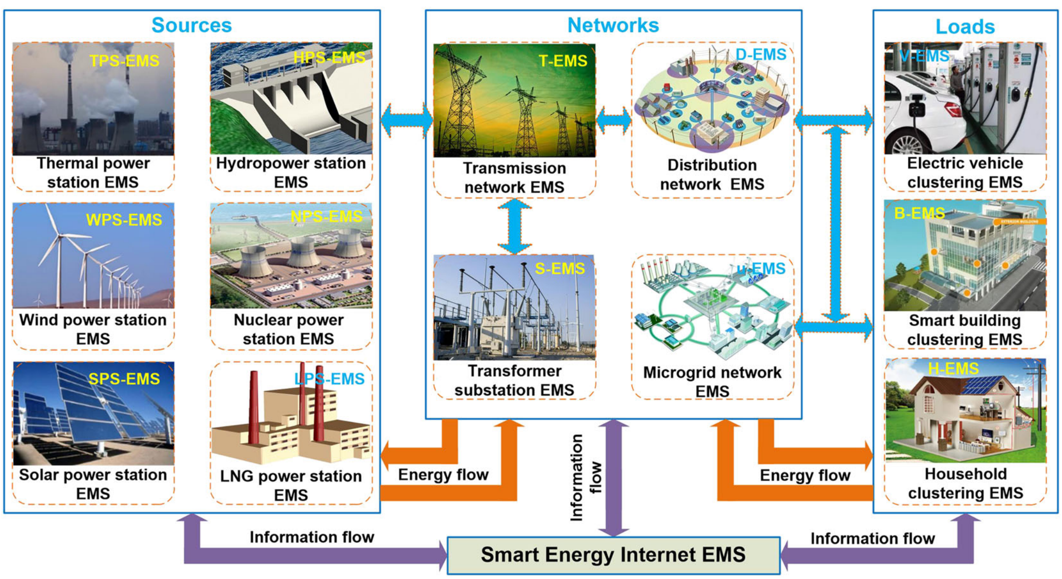

FIGURE 23 The idea of a series of small EMS families in the field of EI represented by the new generation of EEPS [Colour figure can be viewed at wileyonlinelibrary.com]

conducted by group PDRs when meeting the requirements of real-time control and dispatching tasks implementation with different time scales and multiple optimization objectives in multiple regional integrated energy dispatching centers (each of them can see Figure 19).

The investigations of this part are conducted based on the KA of a single PDR elaborated in the precious section. Although the research object of this section is group PDRs, the method of knowledge representation, knowledge storage, and knowledge utilization for them is not fundamentally different from that of a single PDR. Therefore, this part mainly focuses on the collaborative dispatching and control issues of group PDRs (ie, the partition of individual differences and cooperative tasks for those PDRs who are responsible for different regions) as well as the implementation of KA process in the decentralized dispatching manner according to engineering demands. To this end, based on the research work regarding decentralized dispatching and distributed generation control of smart grids, we have already developed some relatively perfect multiobjective optimization models and decentralized optimization algorithms,[76] and among which we have proposed the concept of virtual power generation tribe with decentralized autonomy characteristics, and its relevant decentralized optimization and control algorithms.

Therefore, we deem that the research ideas and research methods in the decentralized dispatching and control of smart grid should be extended to the investigation of the dispatching tasks and real-time control requirements of multiple regional integrated energy dispatching centers on different time scales and with multiple optimization objectives. The details are no longer repeated here.

2. SAS modeling method

In this part, the investigation contents are focused on the dispatching and control issues that are required to be solved via the collaborative work of group PDRs. Therefore, based on the existing decentralized dispatching models and multiagent game algorithms for multiregional integrated energy systems, this section focuses on the decision making and autonomy laws of group PDRs based on game theory and graph theory in the open and ever-growing energy and electric power market environment and the SAS modeling method based on group PDRs. This is the key research content of this section, and also the key technical difficulty and innovation of the whole paper.

In the EI system represented by a new generation of EEPS, the ownership, dispatching responsibilities, and control objectives of each PDR will be different. Hence, in an open and ever-growing energy and electric power market, the decision-making process of the group PDRs is actually the reflection of the social behavior of different stakeholders in the dispatching field. In other words, the decentralized collaboration mechanisms traditionally applied to grid corporations can no longer be well used to explain the complex social behaviors and interactions of different stakeholders. Thus, it is very essential to adopt the concept of artificial society,[5,10,11,15] to remodel the impacts on the interactional relationship between group PDRs. As elaborated in Section 5, the system deployed on top of the parallel system is a real CPSS (ie, an actual cyber-physical-social EI system), and below is a mirrored simulation of this real system (ie, an artificial EI system). The research of AI in artificial life and artificial society belongs to a specialized branch. The relevant research work has made some progress in recent years, but it is far from being used to perform accurate mirrored simulations for real human and real society.

Fortunately, in this paper, we attempt to investigate the behavior of a relatively simple group of PDRs, which involves a small number of individuals. Moreover, the decision-making behavior of the PDRs is constrained by strict physical constraints of the cyber-physical-social EI system and the market rules. Although the SAS modeling of the group PDRs is still a very challenging problem, it is still possible to explore and try to solve such issue relying on various existing mathematical tools. Therefore, in this section, based on the multiagent game theory and graph theory,[87,88] we investigate the construction method and solving algorithm of the SAS model for the group PDRs corresponding to the real human dispatcher group, which lays a foundation for the follow-up investigation of the self-play, self-exploration, and learning of the group PDRs in the EI system. The research methodology of this part is expounded as follows.

First, we investigate the training of the PDR's individual learning, knowledge storage, and behavioral decision-making characteristics. As a mapping of the human dispatcher in the parallel system, the individual PDR can be regarded as an autonomous system that has the capabilities of perceiving external environment and acting autonomously in order to realize its goals predetermined in the system. Therefore, the PDR should be developed with capabilities of external environment perception, self-learning, knowledge storage, and behavioral decision making, as depicted in Figure 24.

Figure 24 demonstrates the principle of the interaction between the individual behavior of PDR and the external environment. Based on Figure 24, from the perspectives of learning ability and behavioral characteristic, we can continuously use the Q-learning algorithm to

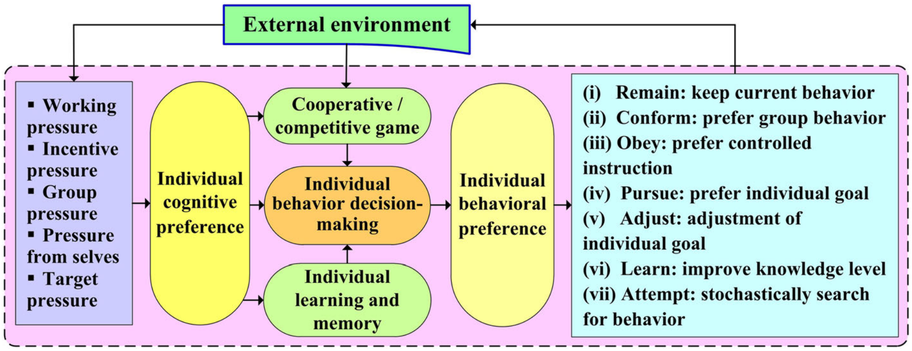

FIGURE 24 Illustration of the principle of the interaction between individual behavior of PDR and the external environment [Colour figure can be viewed at wileyonlinelibrary.com]

develop the capabilities of knowledge learning and knowledge storage for the group PDRs, which can ensure that each PDR operates autonomously and collaboratively. As a result, the environmental information will be converted into reward or punishment signals by the PDR according to its preferences when performing each time of dispatching task, and further implements knowledge learning and memory reinforcement. For the group PDRs, based on their existing knowledge and the external information they acquire, as well as the consideration of the cooperative/competitive game relationships with other PDRs, they will eventually make their own internal state and behavioral choices. During such process, the principle of knowledge learning and storage is depicted as

$$\boldsymbol{Q}_{k+1}(s_k, a_k) = \boldsymbol{Q}_k(s_k, a_k) + \theta\left\{R(s_k, s_{k+1}, a_k) + \vartheta \max_{a' \in \boldsymbol{A}} \boldsymbol{Q}_k(s_{k+1}, a') - \boldsymbol{Q}_k(s_k, a_k)\right\}, \tag{4}$$

where k is the iteration number. $\boldsymbol{Q}$ represents the knowledge or memory matrix of the PDR. s is the state information of external environment. a is the behavioral action strategy of an agent. $\boldsymbol{A}$ is the behavioral action strategy set. R is the reward value of an agent. θ and ϑ are the learning factor and discount factor, respectively.

For some behavioral preferences shown in Figure 24, namely, "(iv) Pursue" and "(vii) Attempt," which can be obtained according to the current knowledge level of PDR as follows:

$$\begin{cases} a_{\text{iv}} = \arg\max_{a \in \boldsymbol{A}} \boldsymbol{Q}_{k+1}(s_{k+1}, a), \\ a_{\text{vii}} = \boldsymbol{A}\{\text{unidrnd}(|\boldsymbol{A}|)\}, \end{cases} \tag{5}$$

where the function unidrnd(n) represents a random generated integer within 1 to n.

Besides, for the behavioral preference: "(i) Remain," which means the PDR's behavioral action strategy remains the same, and for the rest of behavioral preferences (ie, "(ii) Conform," "(iii) Obey," "(v) Adjust," and "(vi) Learn"), which are determined depend on the interaction and cooperation/competition mechanism of PDR with other robots or the external environment.

Second, we investigate the topological modeling method for group PDRs and analyze the social network for them. Generally speaking, complex phenomena are emerged in the artificial system only through the interaction between group PDRs. Therefore, a topology model needs to be established for the social network of the group PDRs. Based on the geographical distribution of EI, the main tie lines between regional power grids are taken as boundaries, and the sub-physical system that is responsible for each PDR is assigned. Hence, according to the interaction network of human dispatchers in the real world, a social communication network among multiple PDRs can be constructed, as demonstrated in Figure 25.

In Figure 25, the social communication network model for the group PDRs can be developed based on the graph theory.[88] In such social network, each network node represents a PDR, and meanwhile the coupling relationships (eg, competitive/cooperative relationship and information transparency) can be revealed by mutual liaison relationships. Based on this, we propose to use three-element mathematical structure to depict this coupling relationship as follows:

$$D = (V(D), E(D), \psi(D)), \tag{6}$$

where D is the digraph. V is the node set that represents the PDR node set. E is the two-element relationship (typically denoted by a directed line segment) that is defined on V. ψ is the mapping function from E to $V \times V$, which can be defined as a multivariate function.

Obviously, the node set V is a PDR node, and E is a PDR's social communication tie line. As mentioned above, the function ψ can be defined as a multi-variable function, in which the information completeness

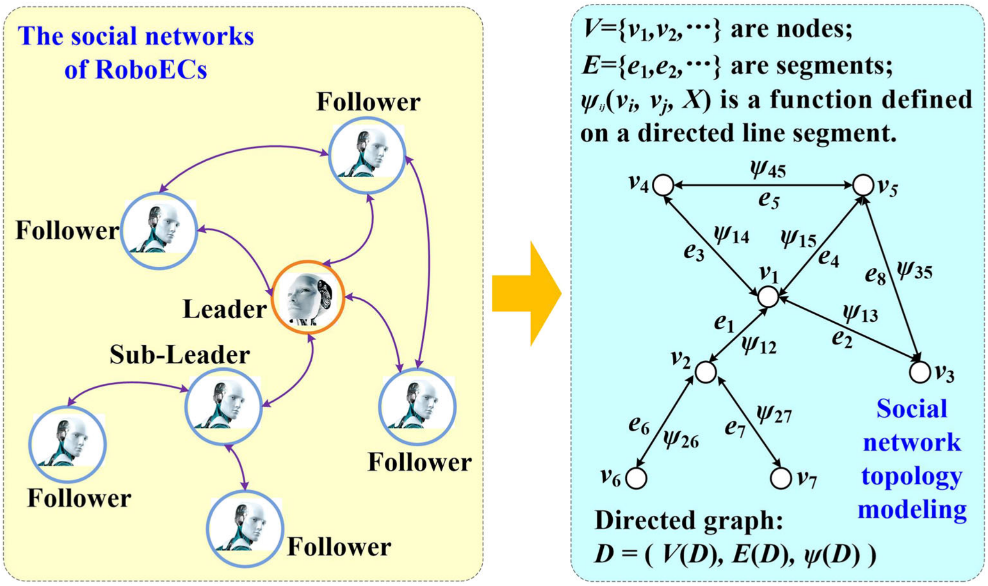

FIGURE 25 Illustration of a social communication network and its topology modeling method among multiple PDRs [Colour figure can be viewed at wileyonlinelibrary.com]

(ie, transparency) and cooperation degree are the two most important variables for ψ. The variation of them between PDRs can be described by the change of liaison relationships in the social network. In addition, it can be concluded from the game theory that when individual information completeness or cooperation degree is different, the corresponding game results (ie, equilibrium points) will vary substantially, as demonstrated in Figure 26.

When the social communication network of group PDRs is modeled by the graph theory introduced in (6), we can easily use the theoretical methods of graph theory analysis to deeply investigate the influence of social communication network changes on the game outcomes between PDRs. Certainly, the equilibrium states and related algorithms shown in Figure 26 can be directly applied for group PDRs research. Besides, the latest achievements of engineering game theories (eg, Cheng and Yu,[54] Yang et al,[72] Liang et al,[73] and Aliabadi et al[89]) can also be referred to.

Based on Figure 26, we still need to investigate the interactive game and evolution relationships between PDRs. In each actual sub-physical system of EI, each PDR often only relies on limited local information to make dispatching decisions. For this reason, in order to enable the entire VPAS to generate a large number of

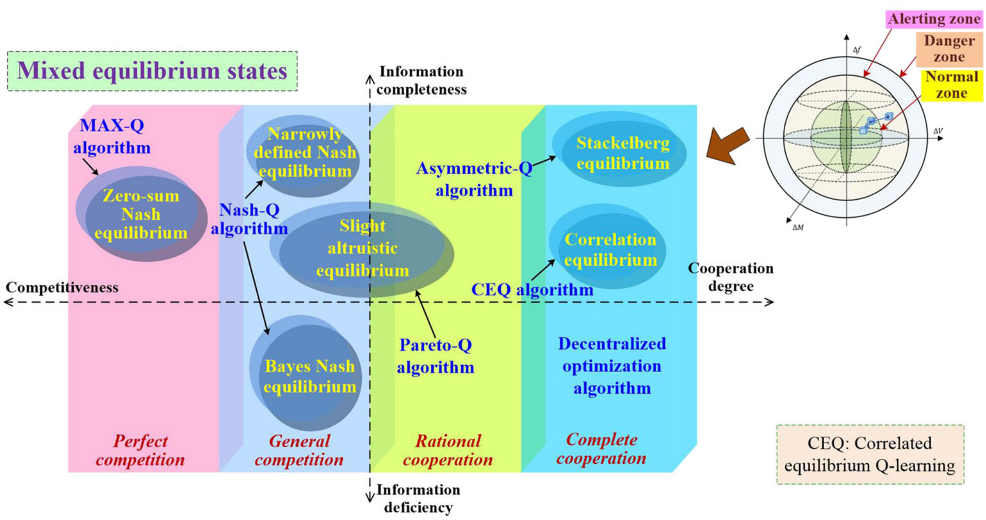

FIGURE 26 Illustration of multiple mixed equilibrium states that may exist in group PDRs, in which each equilibrium strategy corresponds to a kind of multiagent RL algorithm [Colour figure can be viewed at wileyonlinelibrary.com]

qualified and high-quality dispatching strategies (which means economics, security, and environmental protection are all improved), each PDR needs to interact with neighboring PDR based on local information to achieve evolution. To this end, we design a schematic diagram of an interactive game framework, as illustrated in Figure 27.

Based on Figure 27, generally, there are three major types of game issues that need to be addressed for the PDR, including the evolutionary game issue with herd and learning behavior characteristics, the ensemble game issue when considering individual betrayal behavior of PDR, and the predictive virtual game issue under the incomplete information conditions. The following is a brief explanation of the solution to these three types of game issues.

i) *The evolutionary game issue with herding and learning behavior characteristics*: Since traditional Nash games are constructed based on complete rational men assumptions and complete information communication conditions, such that each PDR should have the conditions of complete rationality and complete information to make the optimal decision, which causes issues for the EI dispatching decision making, such as communication bottleneck, low privacy, and difficult in solving. Therefore, we propose to use the bounded individual rationality and information communication based evolutionary game theory to investigate the herding and learning behavior of group PDRs, based on which, the computation in dealing with collaborative autonomy issues of group PDRs can be reduced, such that the artificial virtual system can be easily made to evolve spontaneously toward better dispatching strategy spaces in which multiple optimal equilibrium boundary points can be emerged.

At this point, the evolutionary game theory is a theory that integrates game theory based analysis with dynamic evolution process analysis.[43] In terms of methodology, it is different from the game theory which focuses on static equilibrium and comparative static equilibrium, but emphasizes a dynamic equilibrium. The evolutionary game is premised on the limited rationality of humans, which means that the stakeholders in the game generally cannot or will not adopt the optimal strategy under perfect rational conditions, ie, the strategic equilibrium obtained among the stakeholders or players is often the result of continuous learning and adjustment rather than that of one-time choice, and such equilibrium may even deviate again when it is obtained.

For the investigations of evolutionary game theory, most of which adopts the replicator dynamics equation as the evolution mechanism of the game,[43,90] where the most commonly used updating rules for individual

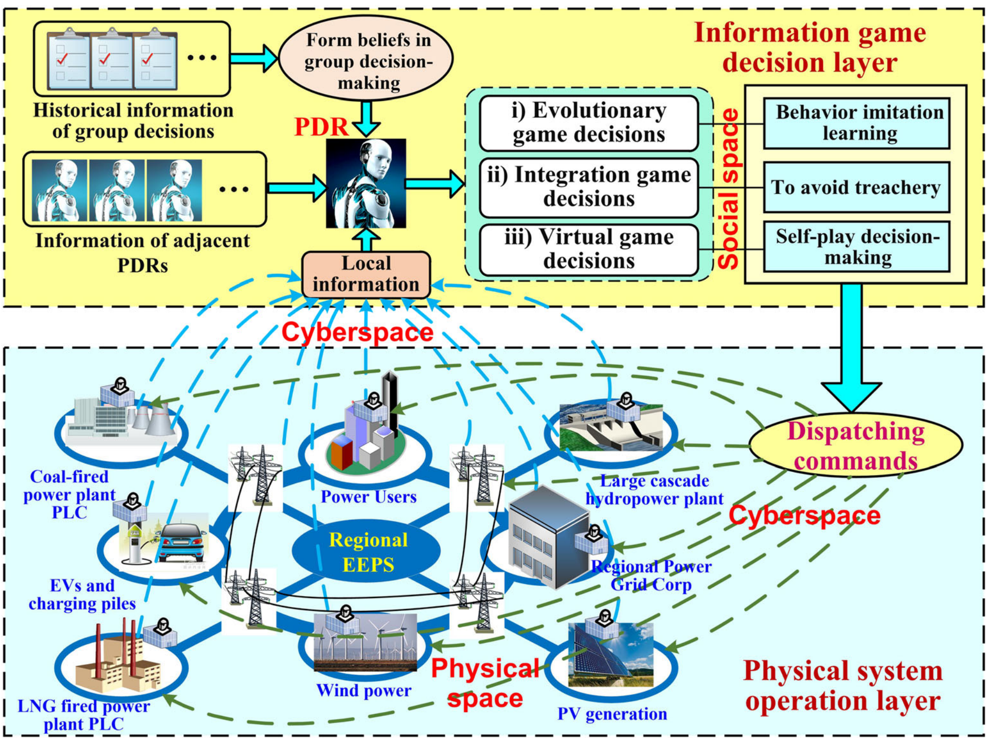

FIGURE 27 A framework designed to depict the interactive games and evolutionary relationships between PDRs [Colour figure can be viewed at wileyonlinelibrary.com]

behavioral action strategies include Fermi process,[91,92] pairwise comparison process,[90] Moran process,[93] and Wright-Fisher process.[94] Now we take the Fermi process as an example, under this rule, the PDR will be able to imitate or directly copy the behavioral action strategy taken by the neighboring PDR, ie, among the group PDRs, the individual i imitates the strategy of individual j with probability p as

$$p(P_i \leftarrow P_j) = \frac{1}{1 + \exp\left[-(U_j - U_i)/\kappa\right]}, \tag{7}$$

where P_i and P_j are the probability of selecting a strategy for individual i and j, respectively. U_i and U_j are the cumulative earnings of the current round for individual i and j, respectively. κ is the noise parameter, and when $\kappa > 0$, representing the possibility of irrational behavior caused by a decision error or external influence, at this point it is generally very small; when $\kappa \to \infty$, representing all the information is drowned out by the noise, at the moment the strategies are updated in a completely random way; when $\kappa \to 0$, representing a definite rule of imitation, that is, when the cumulative income of individual j is higher than individual i, the latter will adopts the strategy of the former.

Besides, we can also adopt the replicator dynamics equation to investigate the evolution games of the group PDRs,[43] in which each PDR will randomly select a neighbor robot for returns comparing after each round of game, and then the neighbor conducts strategy selection with a certain probability p (ie, the difference between two individual benefits), namely

$$p(P_i \leftarrow P_j) = \frac{U_j - U_i}{C}, \tag{8}$$

where the coefficient C is used to normalize the return differences. There are many ways to take this coefficient, for example:

$$p(P_i \leftarrow P_j) = \frac{U_j - U_i}{k_{\max}[\max(T, L) - \min(S, M)]}, \tag{9}$$

where $k_{\max}$ is the larger node degree in P_i and P_j. T, L, S, and M are 2×2 payoff matrix elements.

ii) *The ensemble game issue considering individual betrayal behavior of PDR*: In the process of decentralized dispatching, if some PDRs show betrayed (ie, the group PDRs do not participate in cooperation, but only enjoy returns), then the global artificial energy dispatching system will be easy to be trapped at a poor Nash equilibrium (ie, the overall return is low), which results in a large number of inferior dispatching strategy samples generated in the system. To avoid this issue, a centralized control center can be set up in group PDRs to carry out an integrated strategy review for all PDRs, in which those robots who betrayed will be punished, so that the dispatching strategies of the global system tends to be cooperative and win-win.

iii) *The predictive virtual game issue under incomplete information conditions*: Traditional game models such as Nash equilibrium and correlation equilibrium assume that each PDR can fully acquire the information from other robots such as benefit functions and strategies. However, in an actual game, PDR always executes game decisions with other agents only relying on partial information or historical information, due to the influence from some factors, such as the group PDRs' conflicts of interest, privacy, and noise delay in communication networks. Therefore, we must investigate the predictive virtual game based on incomplete information, which means that an individual PDR can observe the historical selections taken by other robots in the course of repeated games. As a result, based on the acquired historical knowledge, each robot can observe the historical selection of others in the course of repeated games, and use its own subjective beliefs (ie, to simulate the confidence from human beings or a person or thing) to simulate strategic distribution of other participants so as to form a virtual distribution of strategies for other participants, and then according to the rules of virtual action, to implement its own optimal strategic selections, so that the dispatching strategy samples emerged in the system can be approximated to the optimal boundary points. Specific mathematical models and modeling procedures involved in this issue are introduced as follows.

Step 1: We should construct a belief model based on historical information for the PDR. To this end, we can use the typical γ-weighted based belief learning model, which is employed to form beliefs based on historical information of game, that is, the beliefs of the individual i that individual j will select strategy t at the $k+1$ time of iteration is updated as follows:

$$\Gamma_i^t(k+1) = \frac{I_k\left(a_t^j\right) + \sum_{u=1}^{k-1}\gamma^u I_{k-u}\left(a_t^j\right)}{1 + \sum_{u=1}^{k-1}\gamma^u}, \tag{10}$$

where $I_k\left(a_t^j\right)$ is the indicator function, that is, when the individual j selects the action strategy t in the kth iteration, this function is took 1, otherwise 0. The equation (10) as a historical belief function that gives competitors involved the weights of past actions, which decline geometrically. For example, when $\gamma = 1$, for the belief process in a virtual game, the belief in a particular strategy is the frequency that the strategy has been selected in history. This virtual game belief responses more slowly to the action of the previous game than the case of $\gamma = 0$, which refers to that all weights are given to the latest round of action (ie, the Cournot dynamic belief). Obviously, the closer the γ is to 1, the less likely the belief will be to respond to recent selected actions, and the participants will be slower.

Step 2: We solve the predictive Nash-game strategy choice of the PDR. After the construction of belief model, the PDR can make its own action strategy according to other robots' predictive virtual action strategies. When adopting the best response to play game, the best response strategy π_i^* of individual i corresponding to the strategic combination π_{-i} of other PDRs should meet

$$U_i\left(\pi_i^*, \pi_{-i}\right) \geq \max_{\pi_i' \in \sum_i} U_i\left(\pi_i', \pi_{-i}\right), \tag{11}$$

where Σ_i represents the strategy set of individual i. In the strategy combination π, if the strategy of each player in the game is the best response for the strategic combination of all other players, then π is a Nash equilibrium strategy combination.

Step 3: We solve the conservative self-play strategy choice of the PDR. When the PDR adopts the most conservative game mode, that is, minimize the regret value in the worst case so as to avoid greater losses in the future, and then its game strategy can be described as

$$\pi_i^*(s) = \arg \min_{\pi_i \in \Gamma_i(A_i)} \max_{a_{-i}} \left[\Gamma(s, a_{-i}) \sum_{a_i \in A_i} \pi(s, a_{-i}) reg^{a_{-i}}(s, a_i)\right], \tag{12}$$

$$R_{\text{reg}}^{a_{-i}}(s, a_i) = \max_{a_i \in A} \boldsymbol{Q}(s, a_i, a_{-i}) - \boldsymbol{Q}(s, a_i, a_{-i}), \tag{13}$$

where $R_{\text{reg}}^{a_{-i}}(s, a_i)$ denotes the regret value of individual i when performing the action a_i and the other PDRs executing the action set a_{-i} in the state s.

3. PML of group PDRs

In this part, the first step is to investigate the approach to simulate the interaction between artificial societies and physical systems and their natural evolutions to generate massive learning samples in a self-explanation mode, based on which, the ultimate target is to study the advanced PML algorithms for the group PDRs.

In the second step, after completing the SAS modeling of group PDRs, and based on the multiagent game algorithms in VPAS, each PDR will be able to perform PML according to the massive datasets that are generated in the process of interaction between artificial system and real physical system (ie, the virtual and real interaction), as demonstrated in Figures 20 and 22. In addition, in order to achieve the PML of group PDRs, we can adopt a type of ML methods based on three procedures as follows.

First, we use the group PDRs to constitute a multiagent ML system, in which the datasets and learning tasks possessed by each PDR are divided into two parts: (i) completely independent tasks and their datasets and (ii) the tasks and public datasets that need to be done collaboratively.

Second, aiming at an individual PDR that is completely independent, we can use the framework of individual PML algorithm, which can be considered as a decentralized learning.

Lastly, aiming at the tasks that require collaborations between the group PDRs, we also need to introduce the mechanisms of collaborative learning in the parallel learning.

Among the procedures stated above, the decentralized learning mechanism requires that each PDR can perform actions independently according to its acquired datasets. At this point, a certain action a_k of the nth agent can generate a reward $R(a_k^n)$, and its goal is to maximize the overall long-term returns of all PDRs, namely

$$\max_{a_k^m,\, 1 \leq k \leq J,\, 1 \leq m \leq N} \sum_{m=1}^{N} \sum_{k=1}^{J} R^m\left(a_k^m\right). \tag{14}$$

This learning mechanism is suitable for each PDR to perform a relatively independent decentralized control, in which each PDR obtains data and executes actions locally in time-space, or even asynchronously in time. Due to the mutual games and mutual restraints between the group PDRs, an interesting issue arises: whether all the ML processes are bound to converge when executing the maximum goal in (14)? We deem that it may be necessary to use the concept of Pareto-Nash optimum to acquire the expected maximum for the reward of ML of each PDR. Thus, we need to investigate this issue in-depth, ie, investigate the methods of multiagent game to acquire the Pareto-Nash optimal point at which all PDRs as agents are satisfied, and further develop the closely related algorithms.

Under the collaborative learning mechanism, the model of learning leader or subleader who coordinates and guides its followers needs to be established, as shown in Figure 25. The goal of ML is to pick the action a corresponding to the maximum of the rewards that all of these followers may acquire, namely

$$\underset{a_k^m,\, 1 \leq k \leq J,\, 1 \leq m \leq N}{\arg\max} \sum_{m=1}^{N} R^m\left(a_k^m\right). \tag{15}$$

In addition, the collaborative learning can be solved by the framework of multiagent RL algorithms, and it is suitable for solving the issues of Stackelberg equilibrium, as shown in Figure 26.

It is worth noting that the idea of VPAS used in this paper plays a significant role in the construction of EI parallel dispatching system. Based on such parallel dispatch methodology, we can not only imitate various events occurred in the EEPS (this can be regarded as a super-scenario method after extreme expansions), but also assume various variations happen in the social communication relationships between PDRs in the energy and electric power markets. This can greatly compensate for the deficiency that the traditional simulation systems are developed without considering the factors of humans and societies, resulting in a dramatic expansion occurred in the simulative data space. Therefore, the artificial systems can provide a solid foundation for the PDR to perform PML through massive data samples, and eventually surpass the intelligence level of human dispatchers. This is also one of the most prominent advantages for the framework of parallel CPSS developed in the parallel dispatching of the EI.

7 | EXTERNAL GLOBAL LARGE CLOSED-LOOP DESIGN FOR PARALLEL DISPATCH FRAMEWORK OF EI

The investigations in this section can be divided into three procedures. First, we need to study the new feedback control mechanism used in the overall control framework of CPSS-based EI parallel dispatching system (which has been developed and elaborated in Section 5). This mechanism is applied to achieve interactions between the VPAS and real physical system. In addition, we should focus on the key conditions that guarantee the stability of the external global closed-loop system. Second, based on this feedback control mechanism, we need to investigate the ACP approach used in the parallel system, ie, the artificial systems, computing experiments, and parallel execution.[60] This ACP approach can enable the virtual artificial system to guide and coordinate an entity energy system, and ensure the system convergence and stability during the process of virtual and real interaction. Lastly, we should concentrate on the approach to realize a systematic design process in the global large closed-loop CPSS framework. Based on this approach, group PDRs can achieve self-play and PML under this global closed-loop condition. The above three procedures are elaborated as follows.

7.1 | Feedback mechanism and system convergence principle

In this part, we focus on the mechanisms of feedback control and system convergence in the process of virtual and real interaction and coordination between the VPAS and real EI system. The research objective of CPSS is a complex giant system. Although it is hard to provide a rigorous mathematical proof of its convergence,[53] the stability condition of CPSS can be briefly analyzed. As elaborated in Section 5, we have designed two types of feedback mechanism to guarantee the stability of the overall parallel CPSS framework, and they are briefly expounded as follows.

First, we designed an internal small closed loop in the artificial and actual EI systems respectively. This internal loop is seen as an actual stable closed-loop operation system consisting of actual industrial control systems and controlled objects. In this internal small closed loop, since the virtual parallel artificial EI system is treated as a mirrored simulation system of the actual physical EI system, its closed-loop system should be also stable. Therefore, the VPAS will be stable without inputs from the external generalized controller (ie, in a zero input condition). In this sense, the VPAS as a generalized controlled object is a stable and autonomous system. Second, we designed a closed-loop large system, which is mainly composed of three components. The first one is a generalized controller consisting of market orders/market incentives, as well as human dispatchers/PDR instructions. The second is a generalized controlled object consisting of the VPAS. The last one is a generalized feedback loop. Therefore, according to the stability principle of classical control theory, such closed-loop system consisting of the large feedback is not required to achieve the stabilization of the whole system (called stabilization effect), but just plays a similar role of the expected dynamics characteristics design (ie, pole-placement), in which the generalized controlled object can be guided to move toward a better system control target. On the whole, there two key conditions that should be satisfied to guarantee the stability of the entire global large closed-loop system as follows:

The first condition: It is to guarantee the internal stability and autonomy of the generalized controlled object. This means that we need to design a good virtual and real interaction mechanism in the VPAS to ensure that the system stability is not lost due to the interactions in the process of the interaction between the actual physical system and its virtual mirrored system.

The second condition: It is to guarantee a negative feedback, which is formed in the whole closed-loop large system of CPSS, and to ensure that the generalized control law is effective to guide the generalized controlled object to approximate to the predetermined control target.

7.2 | The ACP approach used in the parallel system

In order to satisfy the two key conditions discussed in previous subsection, we need to introduce the ACP approach into the parallel system. Such ACP approach is first proposed by Professor F.Y. Wang, an internationally renowned expert in control field, who provided a framework suggestion that adopt the artificial systems, computational experiments, and parallel execution to form a method used in parallel systems,[10,50,51] ie, an ACP method,[14] as demonstrated in Figure 28.

As elaborated preciously, and based on Figure 28, the real entity EI system can be guided to cooperate with the VPAS. After repeated observations and evaluations by the ACP method, a process of analysis, decision making, and parallel execution with the characteristics of agility (A), focus (F), and convergence (C) can be achieved via virtual and real parallel interaction (ie, the interaction between the artificial system and actual system), called AFC.[10] Finally, the virtual system is used for closed loop and effective control and management of the actual system, such that the convergence and stability of the system can be guaranteed in the process of virtual and real interaction. In fact, AlphaGo can be used to explain how to ensure an optimal path searching among massive virtual datasets. Here, when swarm PDRs eventually find an optimal path in the massive virtual parallel worlds, the global closed-loop system is categorically guaranteed optimal in this hypothetical path. This is also a best interpretation of Merton's laws in complex systems, which can be regarded as a shift from the Newton's systems paradigm to the Merton's systems paradigm (details see Section 1).

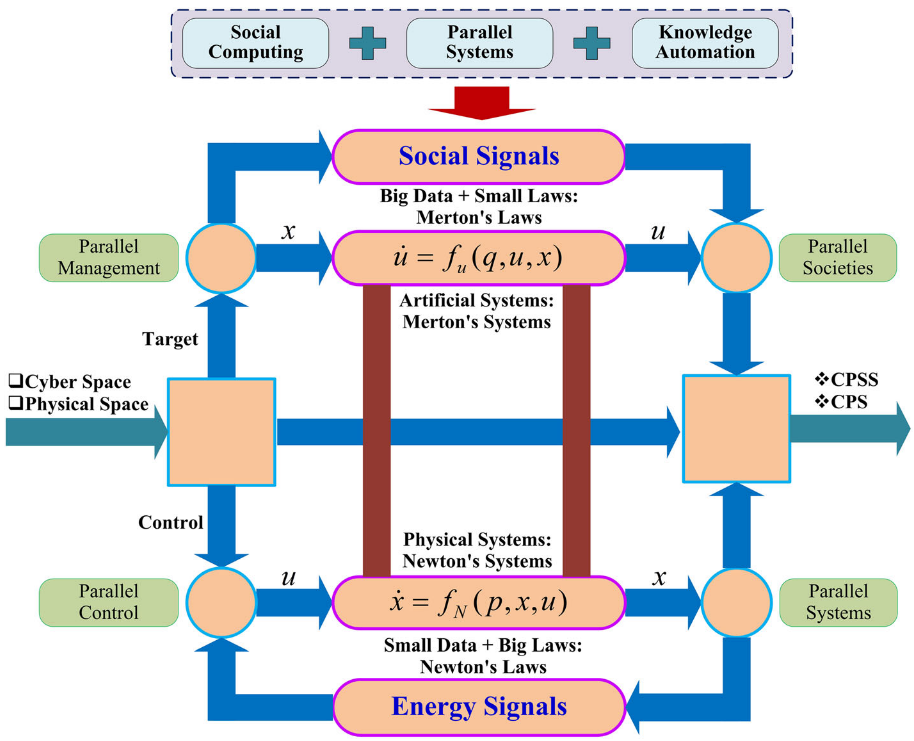

FIGURE 28 The basic principle of ACP approach for complex social energy systems modeling [Colour figure can be viewed at wileyonlinelibrary.com]

7.3 | Systematic design process and implementation method

In order to move forward to the Energy 5.0 system, we have to face a key issue for the future development of the PDR, and that is how to evaluate the direct effect of group PDRs' pre-learning results on stability of the large closed-loop system. Theoretically, the group PDRs can reach the primary level of human dispatcher decision-making capability via offline pre-learning of historical samples (ie, the robots are not put into parallel systems). However, at what stage will the PDR be put into the global large closed-loop CPSS to implement self-play and PML in groups? This still requires a lot of experimental analysis.

Therefore, based on the previous investigations, in the future, we need to investigate the systematic design process and implementation method of the large closed loop of CPSS, based on which, we finally need to investigate the method of self-play and PML methods used by the group PDRs under this large closed-loop condition. In other words, it is necessary to investigate the standardized process of the global large closed-loop CPSS design, which is critical for the future development of PDR, as well as can be treated as an integration of a series of theoretical research results such as the PDR and its KA framework, technologies, and challenges.

8 | DISCUSSION AND PROSPECTS FOR ENGINEERING IMPLEMENTATIONS

8.1 | Discussion

1) Challenges for the future development of PDR

In this paper, we conduct a systematic investigation on the smart dispatching of EI from the perspective of parallel dispatch. Based on the idea of parallel dispatch, we propose the concept of smart parallel energy and electric power PDR based on the framework of parallel CPSS. Besides, we thoroughly investigate the KA and PML techniques involved in PDR. Overall, in this paper, we construct a detailed control framework of PDR for the EI, based on which, we have investigated some key issues, such as KA process, SAS modeling, and PML, to be addressed in the future for the PDR. Hence, we believe that the key technologies involved the PDR include CPSS framework, parallel system, KA, SAS modeling, and software system development. According to these, the challenges of developing PDR in the future are also multifaceted, which are presented as follows:

a. *The challenge from the deep integration modeling of the cyber system, physical system, and social system* (*ie, the CPSS modeling*): It is a main scientific issue that needs to be tackled in future research of PDR for the EI. Although more and more research findings related to CPS have achieved currently, human and social factors are rarely considered in them, while which are increasingly important in CPSS modeling. To this end, these factors are essential to be introduced into the modeling of the large closed-loop CPSS, which is the biggest challenge and risk for future development of PDR. To address this issue, recently, more and more scholars have focused on SAS modeling; thus, it might be an effective strategy to adopt the latest relevant mature research advancement regarding the social behavioral laws and society modeling, and simultaneously, it is of great significance to combine the theory of artificial society modeling with the theories, techniques, and methods of parallel system modeling. For instance, as this paper investigates, we can introduce the latest ML techniques (eg, parallel learning, parallel RL, adversarial learning, transfer RL, and DRL) combining some typical mathematical tools (eg, game theory, complex network theory, and graph theory) into the PDR or group PDRs research, especially, the parallel learning and parallel system theories will play a crucial role in the theoretical investigation of complex system issues, such as the complex cyber-physical-social EI system dispatching issues. Fortunately, the related research work on parallel system and parallel learning has been conducted by Professor Wang for nearly 15 years. For instance, the relevant research results have been preliminarily applied in some industrial fields such as power plant, chemical plant, social energy mining, intelligent transportation system, and intelligent command and control system.[5,13,14,16,52,95] Hence, on the whole, these theories and techniques introduced into the research of the EI parallel dispatching are technically feasible with a relatively controllable risk.
b. *The challenge from the SAS modeling and engineering verification research based on the group PDRs*: Among which, the SAS modeling approach based on group PDRs has been investigated in this paper; thus, we do not repeat it again. With regard to the future engineering verification based on the group PDRs, the supports can be obtained from actual integrated energy demonstration projects, involving software systems and hardware systems development work that will be conducted by us in the future. Hence, one key is to break down the technical barriers to system interconnection and interaction, which can lay a

solid foundation for engineering verification research of group PDRs. In addition, more complicated short-time scale fault dynamic analysis and safety and stability control issues are not involved in the process of PDR research. Therefore, its technical risk is generally controllable due to a good research foundation.

2) Key scientific issues to be addressed in the future

Overall, based on above challenges, we argue that the development of future smart PDR of EI based on the parallel framework of CPSS needs to focus on solving several key scientific issues as follows.

Issue 1: How to build a cyber-physical-social integration system framework that is widely acceptable by the engineering and scientific fields for the EI? This is a basic scientific issue needs to be thoroughly considered from top-level design in study of Energy 5.0. The architecture of Energy 5.0 proposed by Wang et al[5] is still an idea currently. On one hand, the system construction method of CPS still has many difficult issues to be tackled, and on the other hand, when the subjective and emotional factors of human and social factors are integrated into the CPS to form the CPSS, which will face some severe challenges that are uncertain and difficult to reproduce rigorously. Hence, as elaborated in Section 5, firstly, we should try to use the descriptive and fully rational group PDRs to replace human dispatchers, and then use EI based big data analysis and cloud computing technologies to achieve a comprehensive statistical description of human and social factors, so that a feasible framework of parallel CPSS in engineering for EI parallel dispatching can be constructed while the uncertainties of human behavior will be greatly reduced.

Issue 2: How to achieve decentralized autonomy and system self-improvement via the PML of PDRs in groups? This is a key scientific issue that needs to be tackled. The parallel group ML based smart dispatching KA method will be one of the key technologies to address this issue. In addition, the multiagent game theory, especially the evolutionary game theory is another core theoretical tool to reveal the rules of cooperation and competition among the PDRs. Hence, the two approaches can be combined to offer significant innovations but with considerable difficulty.

Issue 3: How to guarantee the convergence of the dynamic process of interaction and coordination between VPAS and real physical system on the basis of mathematical principles? This has been the core issue of parallel system research. It is natural to raise the following question: under what conditions can the mentioned ACP method guarantee the convergence of the large closed-loop parallel CPSS associated with human and social factors? Firstly, the ACP method can be used to evaluate the CPSS, in which the agility, focus, and convergence (ie, AFC) are formed via virtual and real parallel interaction, also called from ACP to AFC. Then, the VPAS based experimental research platform is built to study the conditions that make the PDR move from offline pre-learning to large closed-loop operation. In addition, it needs to monitor the recent advances in parallel system theories, such that the mathematical proof methods for the convergence of interaction and coordination between VPAS and real physical system can be accomplished.

Issue 4: How to improve the engineering practicability of the PDR? Small-scale demonstration projects with multiple complementary energy resources need to be built to verify the implementation feasibility. We believe that it is an arduous step that we must take from theory to practice in the future.

8.2 | Prospect for engineering implementations

1) Exploration on small-scale verification via practice of several demonstration projects

In order to improve the artificial system based experimental research platform of group PDRs designed in this paper, we should attempt to carry out some engineering verification research work in small actual projects which contains various energy resources (eg, small integrated energy systems, small intelligent area power networks,[96] and smart parks). A specific implementation is briefly introduced as follows. The aforementioned integrated parallel experimental computing and simulation platform for smart grid developed based on multiagent JADE (ie, Java Agent Development Framework), Matlab, and GAMS (ie, general algebraic modeling system) has been deployed on the big data analysis platform Hadoop recently, and it has been preliminarily used to try to carry out engineering application research in an EI oriented comprehensive energy management (CEM) technology demonstration project from the CSPG,[33] and which is planned to implement in a certain university located in Guizhou Province, China, as illustrated in Figure 29.

In Figure 29, we have preliminarily completed the configuration tasks in this demonstration project, which means that all online running data, as well as the comprehensive energy management software have been deployed in the project's private cloud. Therefore, we can try to achieve interworking between this private cloud and the private cloud server configured in the built experimental research platform proposed in this paper, which will lay a firm foundation for the virtual and real

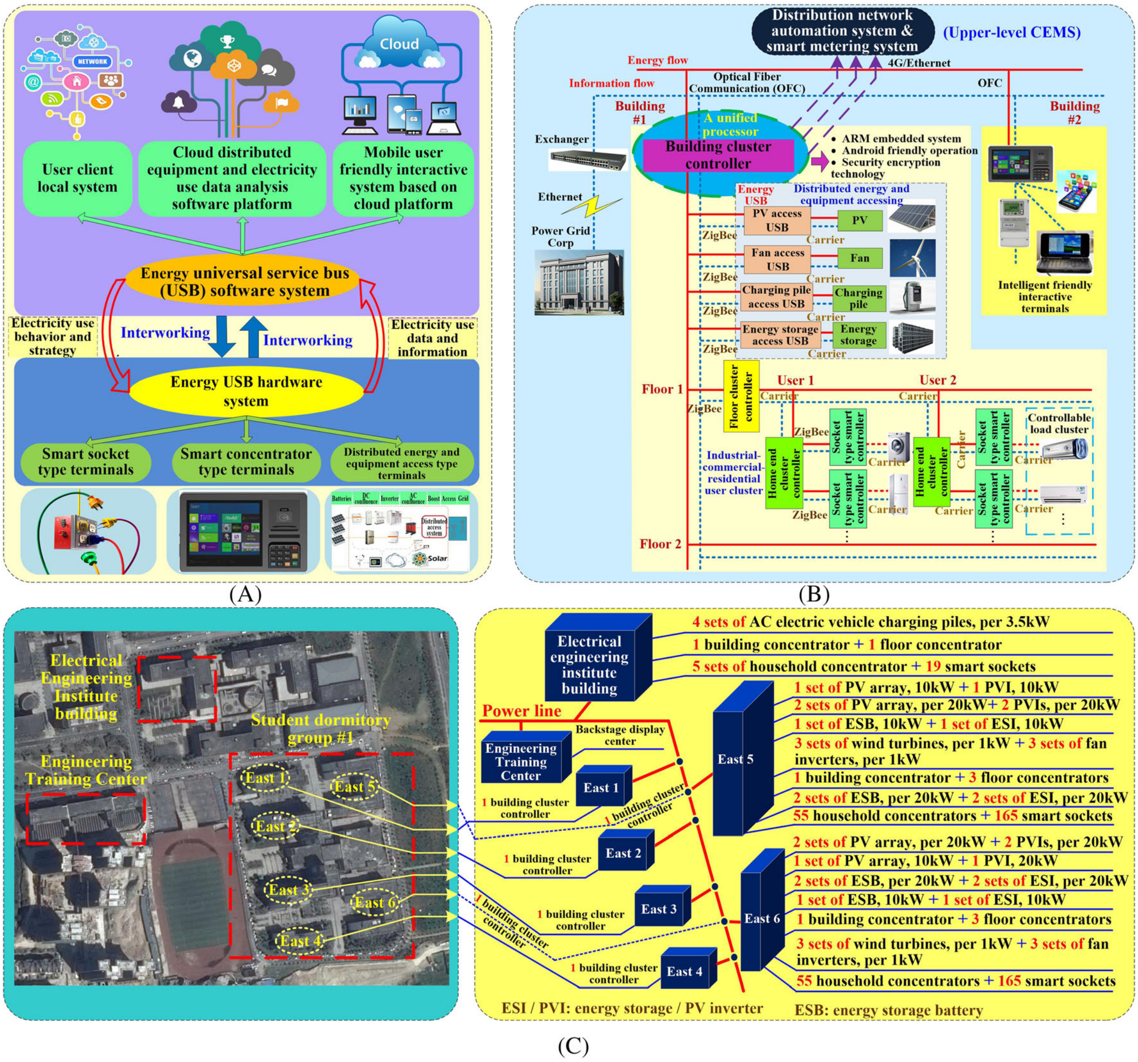

FIGURE 29 The sketch map of the CSPG EI-oriented CEM demonstration project in a university of Guizhou Province, among which (a) gives the overall system architecture design of the energy universal service bus (USB), (b) designs the application topology of the demonstration project, and (c) shows the overall design and installation drawings of the demonstration project application point in a university in Guizhou Province [Colour figure can be viewed at wileyonlinelibrary.com]

interaction between actual physical system and artificial parallel system.

In addition, the first Energy Internet Simulation Laboratory (EISL) of Guangdong Province will be established recently. Accordingly, we can attempt to select some actual physical objects in the PDR as the simulative physical system, to carry out some small-scale integrated demonstration verification research work. We have participated in a demonstration project of comprehensive energy management technology in a certain southern province of China, accordingly, we can attempt to introduce the parallel architecture of CPSS built in this paper into such engineering project, or the aforementioned being built digital-analog hybrid simulation laboratory for EI (ie, the aforementioned EISL), and finally try to put group PDRs into practical system operation for a small-scale engineering verification research.

2) Exploration on simulation verification via constructing a CPSS-based microgrid model based on complex network theory

Based on the experimental research platform constructed for PDR research in Section 5, we have tried to construct a complex network model and a CPSS-based parallel learning architecture to design a support system for group intelligent decision making during the dispatching of EI. In this model, we have adopted the complex network theory to conduct CPSS modeling of a microgrid. Addressed concretely, we adopt the PML method to implement group intelligent dispatching decision making during the process of third-time frequency regulation of the system. The architecture of CPSS integration in this model is illustrated in Figure 30, where the distributed energy management system is an energy center of a typical microgrid, 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).[76]

Based on Figure 30, in order to address the 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 electricity market,[43] we propose to extend the network presented in Figure 30 to a self-organized coupling network,[76] and the relevant investigation on which must be conducted by adopting complex network theory and parallel system theory.[58,76] For this reason, we have carried out some preliminary explanations,[76] among which the small world network model in complex network theory (eg, Newman and Watts,[97] and Newman et al[98]) together with the parallel system theory (eg, Deng et al,[5] Wang et al,[11,52] and Kang and Wang[16]) have been used to investigate the smart generation control of a microgrid, as illustrated in Figure 31. The results are encouraging and indicate that this variable small world network model can successfully avoid the system state falling into a local optimum.[76] Hence, we deem that a more general self-organized coupling network model can be employed for relevant analysis of parallel EI dispatching, and more interesting results will be obtained based on the idea of parallel dispatch in the future.

Currently, the work on analysis and control of complex systems is still the mainstream of international research, especially the enthusiasm of complex system research represented by networked control systems. Through investigations, we find that the systematic and in-depth research on the interaction between humans and the EI has not been conducted at home and abroad. Hence, it is very essential to investigate the human and social factors in the dispatching of complex multienergy coupling systems such as the EI, and the importance of

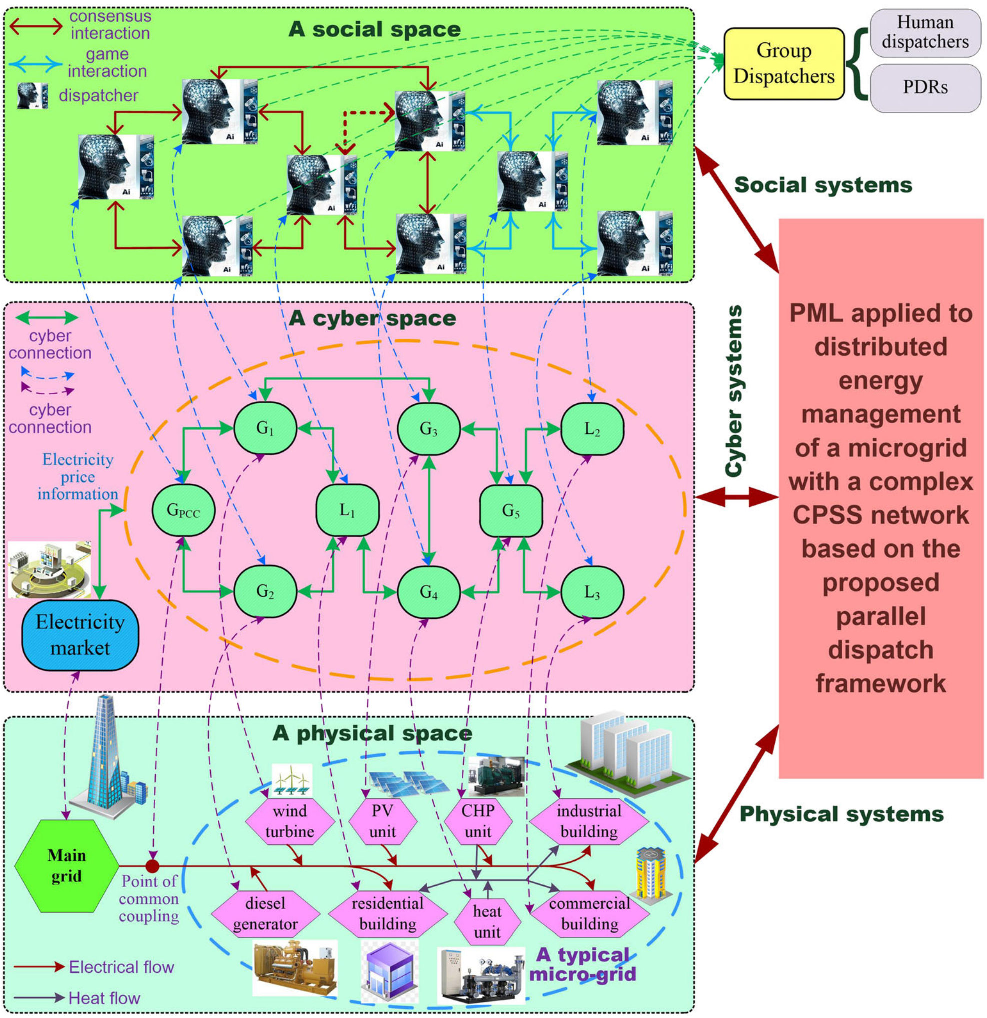

FIGURE 30 The CPSS integration framework design for the distributed energy management in a typical microgrid system [Colour figure can be viewed at wileyonlinelibrary.com]

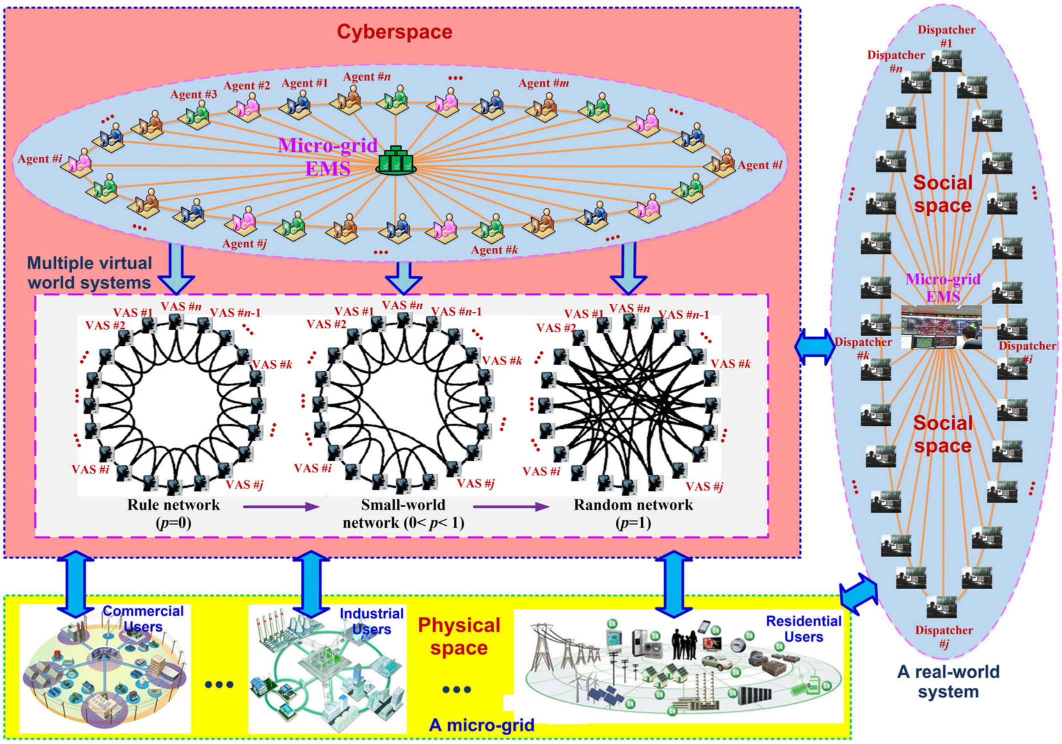

FIGURE 31 The structure of a parallel system for a microgrid based on complex system models such as small world network model, rule network model, and random network model, which demonstrates the learning with multiple virtual artificial systems and a real-world system. In this figure, VAS means a virtual artificial system model [Colour figure can be viewed at wileyonlinelibrary.com]

humans and society to the development of EI (or called social EI). In the future, from the perspective of cyber-physical-social characteristics of the EI, we need to consider the spatial structure and research framework of the multienergy coupling of social networks, so as to establish a multi-disciplinary and multi-dimensional integrated parallel EI dispatching research system.

3) Prospects for research directions of smart dispatching of the EI from the perspective of parallel dispatch and CPSS

In recent years, in the field of smart grid, on one hand, the interaction of human, society, environment, and the grid has been concerned. For instance, some scholars have combined with big data technique to analyze the social and economic conditions and formulate relevant policies through the users' electricity consumption information,[99] and some have used the economics methods to analyze the important role of social benefits in investment and construction of smart grids.[100] In addition, in order to enable the harmonious integration of human, the power grid, and the environment, some scholars also have analyzed the coordination relationship between smart grid and the environment,[101,102] such as reducing carbon emissions. On the other hand, Xue and Yu[103] jointly proposed the energy systems within the cyber-physical-social framework, based which, the impacts of environment, economy, social factors, and human behaviors on the energy chain were analyzed in-depth.

In the future, with the rapid development of a new generation of AI technologies,[56,65] the development of the following four directions will be of great significance to the smart dispatching of the EI from the perspective of parallel dispatch and CPSS, which are briefly introduced as follows.

The first direction: It is the investigation on decision making in the games based on incomplete information conditions. We need to aim at the characteristics of the game under the condition of incomplete information such as human economic activities and man-machine resistance, combine the advances in ML, cybernetics, game theory, etc., and focus on the dynamics mechanism and optimized decision-making model of adversarial game in uncertain complex environments, so as to integrate the adversarial learning and RL with the dynamic game theory so realize the task-oriented general intelligent foundation model and dynamic game decision theory in the incomplete information environment. This is of great significance for the group robots based parallel dispatching under incomplete information conditions.

The second direction: It is the investigation on emergence mechanisms and computational methods of swarm intelligence. For the smart dispatching of complex cyber-physical-social EI systems with high-penetration renewables access to the large-scale power grid, we need to investigate the organizational model and incentive mechanism of large-scale group collaboration in an open, dynamic, and complex environment, in order to establish representable, computable, and controllable compound incentive algorithms. In addition, we need to explore the emergence mechanism and evolution law of individual contribution converging into group intelligence, in order to make breakthroughs in group intelligence evolution method for global targets and time-space sensitive group intelligence collaboration, and finally achieve predictable, guidable, and sustainable group intelligence emergence. This will lay a solid foundation for the smart collaborative dispatching of large-scale group robots in the complex EI, especially for the large-scale decentralized dispatching scenarios, the simulation of emergence phenomena, the automatic mass production of datasets, and the emergence of wisdom of crowds.

The third direction: It is the investigation on man-in-the-loop hybrid augmented intelligence. Human and social factors are increasingly important when dealing with dispatching and control issues in complex EI systems. Hence, we need to investigate the task modeling, environmental modeling, human behavior modeling, and society modeling under the conditions of uncertainty, vulnerability, and openness, develop the man-in-the-loop ML methods and hybrid augmented intelligence evaluation methods, and closely integrate the high-level cognitive mechanism of human analysis and response to complex issues with the machine intelligence systems, so as to effectively avoid decision-making risks and system out of control caused by the limitations of AI technology, and finally achieve human-machine two-way collaboration and solution convergence of complex problems.

The fourth direction: It is the investigation on parallel system theory (including PML theory) and other advanced AI and ML theories, methods, and techniques. Taking parallel system that has been used in this paper as an example, the parallel system refers to a common system consisting of a natural real system and one or multiple corresponding virtual or ideal artificial systems, among which, the PML has three main features: (i) perform big data preprocessing through a software-defined artificial system, (ii) the predictive learning, ensemble learning, and data learning are included, and (iii) implement data-action guided perspective learning based on Merton's laws.[60,61]

Therefore, to sum up, we need to develop the parallel system theory, as well as other advanced AI and ML methods, which will be of great significance to the modeling of CPSS-based smart EI dispatching and control system from the perspective of parallel dispatch, and lay a firm foundation for the development of parallel EI dispatching systems based on single PDR (in centralized dispatching modes) or group PDRs (in decentralized dispatching modes) in the future.

9 | CONCLUSION

It is an inevitable trend of development from intelligent dispatching to parallel dispatching (ie, a PDR). In the past few years, owing to the tremendous increase in the computing power of computers, AI has developed rapidly; thus, making it is possible to use intelligent robots to replace real humans in some domains. Under this background, the complexity of EI dispatching and control, together with the mental pressure of dealing with issues, has reached the tripping point that human dispatchers can handle. Therefore, it is not only technically feasible but also imperative to investigate the smart dispatching for EI. In this paper, focusing on the dispatching issues in the field of EI with a complex CPSS network, we first comprehensively propose a novel conception of smart dispatching for the complex cyber-physical-social EI system from the perspective of parallel dispatch, called PDR. Moreover, we systematically discuss its parallel dispatch framework construction. Based on the investigations on concepts and frameworks of PDR conducted in this paper, we then focus on the implementations of PDR based on SAS modeling.

Overall, the main contributions of this paper are summarized as follows.

i) We first comprehensively propose the novel concept of PDR, ie, the idea of smart dispatching for the complex cyber-physical-social EI system from the perspective of parallel dispatch, which is a major extension and theoretical improvement to the existing single Smart-WAR concept.
ii) Based on the PDR concept and key theories of Energy 5.0, we develop a highly integrated engineering feasible parallel CPSS framework for the parallel dispatching of the multienergy coupled and complementary EI that is represented by new-generation EEPS containing human and social factors. Moreover, in this framework, we first consider the social behavior model of human dispatchers and energy markets as a large closed-loop feedback system in the process of parallel dispatching of the EI.

iii) Based on the framework, we construct an experimental platform containing a VPAS for PDR research, which lays a foundation for the computational experiments of complex EI, automatic generation of massive datasets, and performance improvement of current CPS frameworks in power systems, as well as for the implementation of PDR.

iv) Based on the proposed parallel dispatch control framework, we first comprehensively develop the PML-based SAS models of a single PDR in centralized dispatching modes and group PDRs in decentralized dispatching modes to achieve crowd wisdom emergence and performance improvement in current CPS frameworks of EI. This forms a firm foundation for the generation of large-scale decentralized dispatching scenarios, the emergence of wisdom of crowds, and the implementation of computational experiments of complex EEPS.

v) We completely design an external global closed-loop for PDR to evaluate its operation stability based on the ACP approach. The stability analysis and evaluation on the parallel framework of EI integrating CPSS are still at the simple logical deduction stage, which lays a foundation for the engineering implementation of EI parallel dispatching and control system framework in the future.

vi) We thoroughly investigate the basic theory and methodology of KA for group PDRs based on the framework of PML. The KA process of group PDRs is a process of collective intelligence generation from the single agent to the multiagent knowledge decentralized extraction and storage, knowledge parallel learning, and decentralized parallel solution to the problems, which is a major extension and theoretical improvement to the existing single Smart-WAR concept and a preliminary attempt in investigating a shift from Energy 4.0 to Energy 5.0 in China. In the end, we conduct a detailed discussion on PDR and offer some prospects for its engineering implementations in the future, with the ambitious aims to make the substantial scientific progress from Energy 4.0 to Energy 5.0 in China.

We believe that one of the next research directions should be focused on the mathematical principles, and the feedback control methods and mechanisms employed in the external global large closed-loop feedback system based on the experimental platform developed for PDR research, thus finally achieving the entire system convergence during the interactions between the VPAS and real physical EI system.

NOMENCLATURE

ADNs	active distribution networks
ADP	adaptive dynamic programming
AI	artificial intelligence
AO	automatic operator
ACP	artificial systems, computational experiments, and parallel execution
AGC	automatic generation control
AFC	agility, focus, and convergence
CPSS	cyber-physical-social system
CPS	cyber-physical system
CPES	cyber-physical-energy system
CSPG	China Southern Power Grid
CEM	comprehensive energy management
CHP	combined heat and power
CE	correlated equilibrium
CEQ	correlated equilibrium Q-learning
DRL	deep reinforcement learning
DQL	deep Q-learning
DADP	deep ADP algorithm
EI	energy internet
EEPS	energy and electric power system
EV	electric vehicle
EMS	energy management system
EISL	Energy Internet Simulation Laboratory
FREEDM	Future Renewable Electric Energy Delivery and Management
GDP	gross domestic product
GAMS	general algebraic modeling system
JADE	Java Agent Development Framework
KA	knowledge automation
LAN	local area network
MDP	Markov decision process
MCTS	Monte Carlo Tree Search
ML	machine learning
PDR	parallel dispatching robot
PML	parallel machine learning
RL	reinforcement learning
Smart-WAR	smart wide area robot
SAS	smart artificial society
USB	universal service bus
VPAS	virtual parallel artificial system
$\boldsymbol{A}$	behavioral action strategy set
V	node set
$\boldsymbol{G}, \boldsymbol{H}$	system inequality and equality constraint sets
$\boldsymbol{L}$	energy load vector
$\boldsymbol{\eta}$	efficiency matrix of conversion devices
$\boldsymbol{s}$	coupling coefficient matrix
$\boldsymbol{P}$	energy injection matrix

L_e, L_h, L_g	electric power load, heat load, and natural gas load, respectively
P_e, P_g	electric injection power and natural gas injection power, respectively
v_{ge}, v_{gh}	ratios of natural gas gets through the gas turbine and gas-fired boiler, respectively
η^{e}_{trans}	transformer efficiency
η^{e}_{CHP}, η^{h}_{CHP}	generating efficiency and the thermal efficiency of gas turbine, respectively
η_{Fur}	thermal efficiency of gas-fired boiler
W	optimization objective
W_e, W_c	functional cost objective and carbon emission objective, respectively
$\boldsymbol{f}$	branch power matrix
$\boldsymbol{v}$	node state matrix
P_i	probability of selecting a strategy for individual i
U_i	current round of cumulative payoff for individual i
$\boldsymbol{Q}$	knowledge or memory matrix
s	state information of external environment
a	behavioral action strategy of an agent
D	digraph
R	reward value of an agent
E	two-element relationship that is defined on V
ψ	mapping function of E to $V \times V$
$\boldsymbol{P}_{\mathbf{in}}$	source injection matrix
W	optimization objective
θ, ϑ	learning factor & discount factor, respectively
k	iteration number
i, j	individual number
C	a coefficient for normalizing payoff difference
$I_k\left(a_t^j\right)$	indicator function
Σ_i	strategy set of individual i
π	strategy combination
$R_{reg}^{a_{-i}}(s, a_i)$	regret value of individual i when performing the action a_i and the other PDRs executing the action set a_{-i} in the state s

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