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A review of machine learning for new generation smart dispatch in power systems☆

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ABSTRACT

This paper analyzes the characteristics and challenges of the new generation smart dispatch systems, and proposes the framework of smart dispatch. Secondly, the development of the new generation artificial intelligence technology is represented, especially the development of machine learning algorithms. Thirdly, the applications of machine learning in power systems, e.g. smart generation control, optimal power flow, security assessment, smart dispatch, are listed. Finally, the framework of dispatching robot technology based on parallel learning is present.

1. The characteristics and challenges of the new generation smart dispatch systems

Nowadays, the potential development of artificial intelligence (AI) has made the competition growing fierce in the field of AI. The attention of AI is rapidly increasing, AI has brought new opportunities for the whole society and an ocean of unprecedented challenges. *The European Association for Artificial Intelligence* explained the true potential of the AI technology, and focused on its transparency and reliability of AI (Cath et al., 2018). *The White House* (American) hosted the industry summit of AI, discussed the development trend and strengths of government, industry, and academia, and promised U.S. leadership for American people in the age of AI (House, 2018). *The State Council* (China) issued a notice on new generation development plan of AI in 2017 (Council, 2017). The notice is designed a complete blueprint for the development of AI in the next ten years. For example, the development of AI in China could enter a new stage by completing three objectives as follows Li (2018).

Objective one: by 2020, the development level of AI could be in line with the world advanced level in China. The development of AI in China contains two aspects, i.e., theories and applications. The theoretical level contains swarm intelligence, autonomous intelligent systems, big data intelligence, hybrid enhanced intelligence, cross-media co-processing, etc. The application level contains basic software, advance equipments, core devices and AI modeling methods, etc.

Objective two: by 2025, the theoretical researches and practical applications of AI could partially lead the world level with breakthrough theoretical results in China. China is actively building an intelligent society, and allowing AI to participate in economic transformation and industrial upgrading. Then, China will have higher degree of intelligence in defense, industry, agriculture, health care, and urban construction. The scale of AI core industries could large than 400 billion RMB (the official currency of China), and the scale of related industries could large than 5000 billion RMB (Cheng et al., 2016).

Objective three: by 2030, AI could achieve great development and prosperity in China. China could become an important international research and development center of AI, which has profound impact on the development trend of international AI. China gradually achieves the goal of becoming an economic power by developing intelligent economy. China could gain the advantage in the competition of the world's innovative country by developing intelligent society. Numerous fields could have breakthroughs, such as swarm intelligence, hybrid intelligence, autonomous intelligence and brain-like intelligence.

The new generation AI is mainly affected by the following factors (Li et al., 2018),

(1) Information, physics and society are closely linked and fused to produce large amounts of data.
(2) The computing ability of computers has been greatly improved, and the data processing technology has been improved greatly with the rapid development of computer hardware and software technologies.
(3) Intelligent algorithms (e.g. deep learning and reinforcement learning) have achieved massive research results and made great

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breakthroughs in the field of control theory and optimization theory.

(4) The development of AI could be affected by massive investments, relevant policies, and social sectors, etc.

AI entered new age of development, and emerged different ideas and goals. The direction of AI based on theoretical research had undergone important adjustments (Gil et al., 2004). Deep learning, reinforcement learning and other technologies have reached the stage of rapid development from the initial stage.

The unstoppable industrial development is rapid, resulting in a large number of energy consumption and waste, which puts forward higher requirements for the transformation of energy supply mode and the algorithm of energy planning (Wu et al., 2016). With energy revolution from energy 4.0 systems to future energy 5.0 systems, industrial systems will be enter into future industrial 5.0 systems from industrial 4.0 systems (He et al., 2016; Wang, 2016). Moreover, the rage of algorithms for optimizing energy allocation and controlling will be multi-domain fusion algorithms from single optimization and control algorithms.

The power systems are constantly being upgraded with the development needs of the industry, and the power grids could be more intelligent, thus entering the age of the power grids 2.0, i.e., the age of smart grids (Pan, 2016). Furthermore "Energy Internet" (Wang et al., 2018) and cyber–physical systems (Lee, 2015), even cyber–physical–social systems (Lee, 2008), may appear in the future.

Compared with conventional power grids, the characteristics of smart grids integrated with industrial intelligence could be summarized as follows,

(1) Smart grids could have stronger robustness.
(2) Smart grids could manage more distributed energy sources.
(3) Smart grids could carry out coordinated economic regulation of multiple energy sources.
(4) Smart grids could have comprehensive network information, and the modes of the networks of smart grids will be more flexible.

Various countries are building smart grids with the development of renewable energy sources and distributed energy sources (Fang et al., 2012). Therefore, the accesses of various renewable energy sources and intermittent energy sources lead to external disturbances and increased internal parameters, which will bring the dispatching problem of smart grids (Yaozhong et al., 2015). China has begun to build strong smart grids with Chinese characteristics in 2009, and the smart grid could add more design concepts in the future (Zhang et al., 2010). But for now, the designs of the smart grids should take full account of electricity prices, plug-and-play, electricity market, environmental protection, natural disasters, user participation, accident prevention, power quality assurance and self-healing, etc. Li et al. (2017a).

In the background of vigorously developing smart grids, smart dispatch has ushered new challenges in the following five applications.

(1) The challenges brought by various forms of energy sources continuous access to smart grid: the accesses of distributed energy sources, intermittent energy sources, random energy sources, and controllable flexible loads will bring challenges for smart dispatch, such as large-scale access to wind farms, customer-side wind and solar storage complementary systems, biomass generation, and accessible electric vehicles (Liang, 2017).
(2) The challenges brought by power market reform: as the pace of power market reform progresses, the game (game theory) between generation companies, transmission companies, power sales companies, and customers of electricity are constantly expanding. Ensuring multi-party benefits in the optimal configuration of energy sources creates certain challenges for smart dispatch (Ruhang et al., 2018).
(3) The challenges brought by changing the systems framework: with the upgrading of smart grids equipment and the blurring of control areas, virtual power plants are constantly being investigated and applied, and even the exploration of virtual generation tribes. The structures, topologies and operation modes of smart grids could occur large changes, which bring challenges for smart dispatch (Kristiansen et al., 2018).
(4) The challenges brought by changing in the internal parameters of the systems: model-based algorithms, long-timed algorithms, algorithms that cannot be updated on-line, and algorithms that cannot adapt to changing system parameters could not be applied in actual automatic generation control systems, which brings challenges to smart dispatch.
(5) The challenges brought by increasing control objectives: with the increasing of control objectives (e.g. power quality objectives, economic objectives, and environmental objectives), the existing control strategies could not be simultaneously meet the requirements of multiple objectives, which brings challenges to smart dispatch (Wang et al., 2018b).

2. Framework of smart dispatch of power systems

From the time-scale perspective, the smart dispatch problems of power systems can be divided into the real-time multi-objective programming problem and the prediction problem. For example, when solving real-time smart travel planning problems, smart dispatch needs to predict various types of problems and plans reasonably with the prediction results (Lyons, 2018), mainly including passengers travel destination forecast, total travel time estimate, future market demands and supply forecasts, etc. Chai and Chen (2018). The perfect combination of multiple time-scale could lead to non-economic dispatching in smart dispatch of power systems. Then, power systems are huge delay systems, the control problems of generator sets should be considered with the features of generators or power plants (Wang et al., 2018c). Therefore, power system smart dispatches are real-time control and forecasting integrated into the smart dispatch and control systems.

Distributed renewable energy sources and flexible loads are increasing accessed to power systems which affect the security and stable operation of power grids by uncertain factors (Twaha and Ramli, 2018). In addition, natural disasters and external forces have been frequently appears (Chen et al., 2016). External extreme disasters are increasing to power grids, and could cause widespread cluster failures and endanger operation of power grids (Lei et al., 2018). To keep the security and stability operation of power grids, *Electric Power Research Institute* (American) has proposed dispatching control system of smart grids, which must have the characteristics of self-healing, interaction, optimization, prediction, coordination, and integration at least (Utilization, 2012). The "father" of dispatch automation, who is T. E. DyLiacco, proposed the concept of "smart dispatch robot", which means smart grids operation rules adapt to the on-line operation mode, realize the smart accurate dispatch of smart grids, and improve the operational efficiency of smart grids (Shan et al., 2018).

As shown in Fig. 1 , the total framework of smart dispatch is applied to build a model cloud based on demand-side services smart grids, provides model support for efficient stream processing, data mining, and fault diagnosis in smart dispatch center, and finally forms new human-machine systems of visualization and interaction (Xu et al., 2018).

3. New generation AI technical development overview

AI has four distinct developmental periods. The concept of AI was first proposed at the Dartmouth conference in 1956 (Kline, 2011). The basic theory of AI was gradually formed by 1974 (Müller and Bostrom, 2016). Then AI entered the knowledge processing period, which means systematically study knowledge engineering and expert

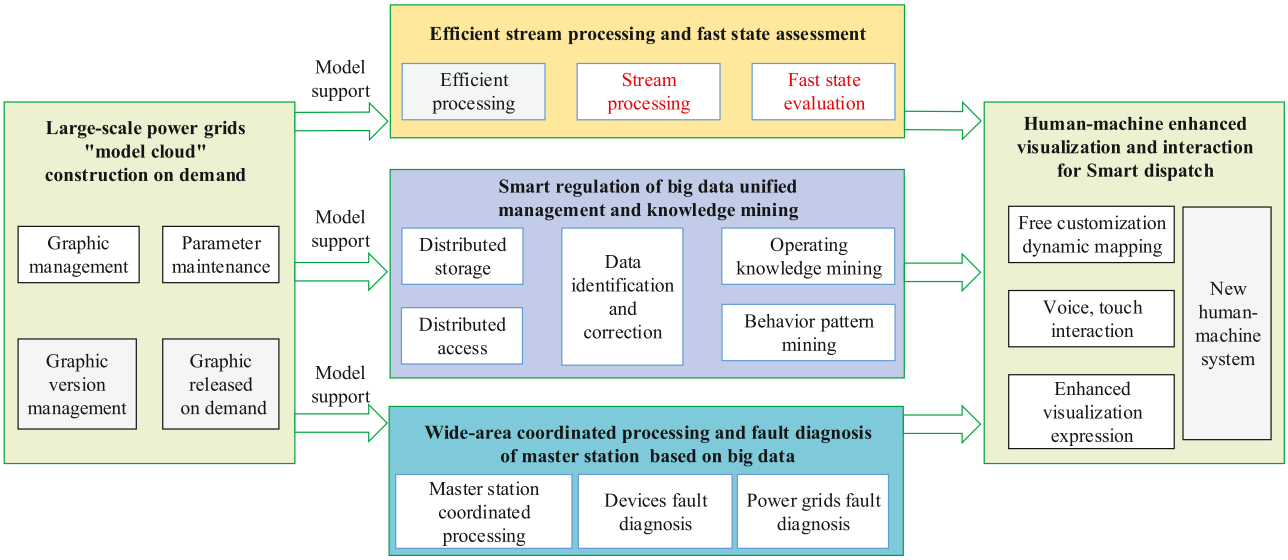

Fig. 1. Total framework of smart dispatch.

systems (Glover, 1986). The most important feature was statistical learning in the beginning of the 21st century, which was the characteristic processing period of AI (Frishammar, 2002). Nowadays, AI has developed into the data processing period, the characteristics of the period allow the machine to extract features from the original data for learning, rather than artificially designated or extracted features. Obviously, the current period has great progress in technology (Li et al., 2017c).

The new generation AI mainly has the following characteristics (Cheng and Yu, 2019).

(1) Big data play a key role in the sustained and rapid development of AI.
(2) Voices, images, texts and other information could be achieved media interaction.
(3) Networks are utilized to realize the development of individual intelligence to swarm intelligence.
(4) Autonomous intelligence systems could be full developed by AI.
(5) The new hybrid intelligence appears in the background of human-machine cooperation.

The year of 2016 could be regarded as milestone in AI. AlphaGo has been developed by Google's DeepMind team, and defeated the world's top player Lee Se-dol 4:1 with the game of Go (Borowiec, 2016). AlphaGo's upgraded version (Master) defeated top Chinese and Korean professional players including the world's number one Jie Ke, creating a 60:0 victory record in 2017. AlphaGo Zero has been published in *Nature* in October 2017 (Chen, 2016). AlphaGo Zero no longer relies on history of the Go of human confrontation to learn, rather than explores itself from zero, i.e., "pure reinforcement learning". AlphaGo Zero has been obtained an overwhelming record of the Master 100:0 by "pure reinforcement learning" with three days training, which makes more people aware of the power of reinforcement learning (Silver et al., 2017). The game of Go is conventional knowledge learning and real-time decision-making process. Generally, the game of Go has been regarded as the representative of the highest human intelligence. AlphaGo's victory means that AI could replace almost the industrial automation systems or other fields that people intervene in technology (Wang et al., 2016).

Originally from 1989, Yann LeCun, who is the professor at New York University, applied convolution neural networks to solve image recognition problems, which is the earliest application of deep learning (LeCun and Bengio, 1998). In recent years, deep belief networks (DBNs) based on deep learning was proposed by G.E. Hinton et al. DBN is an algorithm based on neural network with multiple hidden interpretation coefficients by superimposing several restricted Boltzmann machine models (Hinton, 2009). DBN has various improvements since its development, such as sparse deep belief networks (Lee et al., 2008), conventional deep belief networks (Lee et al., 2009). Deep learning has rapidly evolved into a tool with powerful feature recognition capabilities and breakthroughs in speech recognition, gaming, industrial control and other applications.

Iflytek, which is a leader of intelligent voice industry in China, participated in numerous domestic and international speech synthesis evaluations (Liu et al., 2017). Iflytek evaluation indicators are the top in terms of smart voice interaction in the world (Zhu, 2019).

Virtual reality is an interaction technology of human-machine that simulates the visual, tactile, and auditory sensations of the real world (Tamura et al., 2001). Virtual reality has great user experience because it creates a virtual world similar to the real world. Mixed reality is an upgrade based on virtual reality technology (Jung et al., 2016). Mixed reality constructs information feedback loop interactively between users, real world and virtual world, such as real power systems and virtual power systems. Mixed reality enables the experience immersed into the real world and feels the real scene information in the virtual world (Pan et al., 2006).

Adding emotional coefficients to AI is the direction of future AI development. At present, there are three core problems (emotional behavior gathering, emotional recognition, and human-machine emotional communication) (Mayer and Geher, 1996) in the implementation of AI with emotional factors. The goal of emotional recognition is mainly based on implicit information (Valstar et al., 2016), and emotional recognition major includes artificial emotion, kansei engineering, affective neuroscience, etc. (Gong and Wang, 2011). The machine could recognize human emotions because the machine collects and analyzes the data of the customers with the computing power and built-in algorithms (Zhang et al., 2018a). The machine utilizes the ability of recognize human emotions to communicate with the customer in turn. Emotional analyses could identify the relationship between humans in the group by facial expression, gender, distance information, facial similarity and other information (Li et al., 2019). In addition, the machine could recognize the age and the match clothes of person, and makes age judgment of the overall visual from the face to the clothes (Gomes and Preto, 2018). Researches on machine emotions are still studying emotional behavior gathering and image recognition technology (Li et al., 2017c). Although AI already has some low-level emotions, achieving unbiased emotional communication still needs the unremitting efforts of researchers.

In summary, AI overall classification framework is given in Fig. 2.

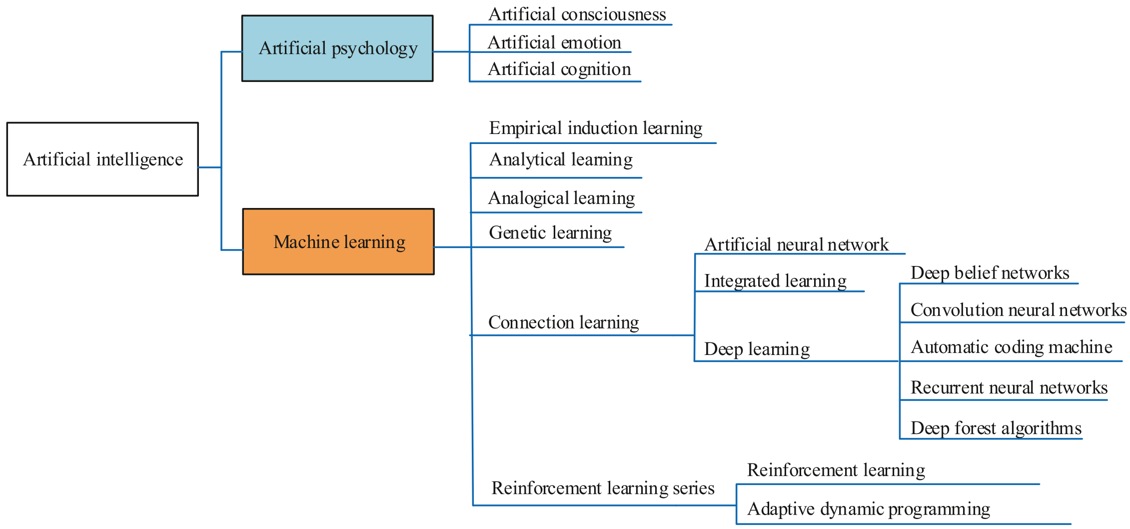

Fig. 2. Total framework of artificial intelligence.

4. Applications of machine learning in power systems

To solved energy crisis, the massive introduction of renewable energy is requested. Distributed energy and plug in hybrid electric vehicles constantly accesses power systems, more excellent smart generation control should receive attention (Zhang et al., 2017). Due to the uncertainty of renewable energy sources, higher required constraints and easier constraints relaxes are imposed on optimal power flow. The study found that the beginning of a blackout accident is often accompanied by a transient fault (Sadeghkhani et al., 2018). Once the power dispatch control cannot be corrected security assessment in time, the stability of the grid will be destroyed, which is easy to develop into a follow-up cascading failure, resulting in a large-scale malfunction. Therefore, in this section, the paper will display key subareas, including smart generation control, optimal power flow, security assessment, smart dispatch, in power systems.

4.1. Applications of machine learning in smart generation control

The concept of smart generation control has been proposed by Tao Yu, who is the professor at South China University of Technology (Yu et al., 2016). Compare with automatic generation control, smart generation control is more efficiency for distributed energy, which in line with the characteristics of the smart grid (Kakran and Chanana, 2018).

Machine learning has been popular in smart generation control, such as a relaxed deep learning has been proposed for the real-time economic generation of multi-area interconnected power systems (Yin et al., 2018). Y. Seyedi and H. Karimi proposed coordinate strategy with data processing and improved situational awareness in smart distribution networks (Seyedi and Karimi, 2018). The controllers are significantly to completing voltage control. Compared with conventional proportional–integral–derivative, the optimized controllers based on meta-heuristic firefly algorithm can obtain higher control performance (Shaukat et al., 2018). The firefly algorithm has been applied to different scenarios through simulations, and the controller and systems performances were verified (Chaurasia et al., 2017). Coordinated voltage control has been employed to smart distribution networks (Kulmala et al., 2014), and in-the-loop simulation method has been proposed for coordinated voltage control algorithms, which supports the effectiveness of smart algorithms in smart generation control (Maniatopoulos et al., 2017).

The smart generation control strategies mainly include reinforcement learning algorithms series (Yan et al., 2017), such as Q learning algorithm (Watkins and Dayan, 1992), Q(λ) learning algorithm (Harutyunyan et al., 2016), R(λ) learning algorithm (Tao Yu, 2012) and win-or-learn-fast algorithm (Jintian and Lei, 2009), adaptive dynamic programming (Lewis and Vrabie, 2009). The reinforcement learning algorithm is a model-free algorithm, and higher control performance indicators could be obtained by reinforcement learning algorithm under external disturbances (Irfan et al., 2017). Reinforcement learning algorithm has widely improved due to the agent base on reinforcement learning could update the control strategy on-line. For example, reinforcement learning algorithm based on artificial emotion is applied interconnected large-scale power grids (Yin et al., 2017), Q learning algorithm based on distributed correlation equilibrium is represented under coordinated multi-agent systems for smart generation control (Yu et al., 2015), SARSA algorithm based on the 5-component, i.e,state–action-reward-state–action (Wang et al., 2013), and SARSA(λ) algorithm improved by eligibility traces, which optimizes power system stabilizer to suppress low frequency oscillation in power systems (Yu and Zhen, 2011), policy-dynamics based win-or-learn-fast algorithm (Bowling and Veloso, 2002), and policy-dynamics based win-or-learn-fast policy hill climbing (λ) algorithm is employed interconnected complex systems for smart generation control (Xi et al., 2015).

Numerous methods can be developed to improve the adaptive dynamic programming, and the algorithm application scenarios are extremely extensive. For example, adaptive dynamic programming control of power grids voltage and energy storage systems (Das and Akella, 2018); goal representation heuristic dynamic programming control of wind power frequency (Tang et al., 2015); multi-agent transaction principles automatic navigation demand control for integrate renewable energy through adaptive control algorithm (Prinsloo et al., 2018); D. Villacci proposed a novel method based on adaptive local learning, which has been applied into the voltage regulation of distribution networks (Villacci et al., 2006); L. shiyang proposed on-line voltage stability margin monitoring method based on local regression and adaptive database (Li and Ajjarapu, 2015); cascading approach based on machine learning algorithms is a distributed architecture, which means different machine learning methods for different incidents in secondary voltage control (Karim et al., 2016).

4.2. Applications of machine learning in optimal power flow

One of the most important technical and economical tool in smart grids is optimal power flow (OPF). As a fundamental optimization tool in the operation of power systems, OPF could optimize simple or multiple of performance indicators by adjustment control variables (Abdi et al., 2017). Dominant Pareto solutions for multi-objective OPF has been obtained by multi-objective modified imperialist competitive algorithm (Ghasemi et al., 2014), Gaussian Bare-bones multi-objective imperialist competitive algorithm (GBICA) and modified GBICA (Ghasemi et al., 2015). In early research, genetic learning algorithms have been applied to OPF, such as improved genetic algorithm (Lai et al., 1997), enhanced genetic algorithm (Bakirtzis et al., 2002), and immune genetic algorithm (Yulong et al., 2008). For dynamic data, OPF based on genetic learning algorithms has various limitations. To solved the limitations, genetic algorithms based on similarity adaptive learning have been employed in reactive power optimizations (Hong et al., 2007), adaptive strategy proposed in distribution systems with renewable energy sources (Dall'Anese et al., 2017) and fuel efficient operation (Satpathi et al., 2017).

Based on the theory of reinforcement learning, Dayong Ye proposed a coordinate each reactive control device with Q(λ) learning algorithm, which has been applied to complete the global optimal control strategy in local power grids (Ye et al., 2011). Yujing Hu proposed a correlation equilibrium reinforcement learning synergy algorithm (Hu et al., 2015), which realizes OPF and multi-region information sharing. Min Tan and Tao Yu proposed hierarchical correlation equalization Q learning algorithm, which has been applied to improve the global search ability and convergence speed for the OPF (Tan et al., 2016).

Consider the chance constrained programming of OPF, a simple optimization formula has been obtained by reformulation chance-constrained alternating current optimal power flow(ACOPF), which can solve deterministic problem by iterative approach and assess the impacts of uncertainty (Roald and Andersson, 2018). The ACOPF considers the relevant variables of the chance constraint, and determines the corrective control strategy (Venzke et al., 2018). The uncertainty operation of power systems has been modeled and corrected by Roald et al. (2017). D. T. Phan proposed a novel model for the security-constrained optimal power flow (SCOPF) problem with direct current power flow constraints, and SCOPF model corrects accidents through sparsity regularization technology in Phan and Sun (2015).

Convex relaxation algorithms have been utilized to convert the OPF into semi-definite programming and obtained global optimal solution in integrated alternating-direct current grids (Bahrami et al., 2017). Convex relaxation algorithm has been applied into ACOPF in distribution networks, and the optimal solution of the second order cone program could be transformed into the optimal solution of the original ACOPF (Huang et al., 2017). D. Wu introduced relaxed variables to convert the inequality-constrained ACOPF problem into an equality-constrained problem by an elliptical form (Wu et al., 2018). Convex sufficient condition, convex relaxation and approximate model have been employed in voltage stability constrained OPF (Cui and Sun, 2018). An adaptive robust optimization model has been employed into ACOPF, which can solve non-convexity in the power flow equation and uncertainty in renewable energy sources (Lorca and Sun, 2018).

In the smart grids operation of OPF (Fig. 3) (Xu et al., 2018): in the automatic cruise system, the model of the sources and loads uncertainty are built by interaction mechanism (Doerry, 2015); machine learning algorithms have been introduced multi-objective economic OPF to obtain optimal operating points, such as reinforcement learning, chance constrained programming, convex relaxation algorithms; the collaborative optimization of the sources and loads has been completed; reactive power control methods and distributed power grids control strategies have been determined.

4.3. Applications of machine learning in security assessment

With the development of grid interconnection and the implementation of the electricity market, a great conflict of security and economy has arisen in power systems. Under such uncertain operating conditions and complex controls, security assessment of power system has been particularly important.

The machine learning method is a natural data analysis tool, which is suitable to complete feature extraction and modeling. The main purpose of static security assessment (SSA) is finding voltage limits and maximum source and load access in economical operation of power systems. To design the static security assessment (SSA) of power systems, Sekhar achieved security classification by decision tree and random forest model (Sekhar and Mohanty, 2016). The cost-sensitive decision tree algorithm has been employed to class static power systems imbalance data (Guney and Tepe, 2017). The improved simplified binary tree support vector machine (SVM) has been applied to the SSA of photovoltaic power systems (Saeh et al., 2016). Modified particle swarm optimization, differential evolution, ant colony optimization for continuous domain, and harmony search have been employed for determining the optimal SVM parameters, and SSA is divided into four types of corresponding level of warning (Rastgoufard and Charalampidis, 2016; Zhang et al., 2012).

Transient faults in the power system could easily cause large-scale power failure. To avoid the failure, the dispatch center complete the prediction and control by establishing transient stability assessment (TSA) (Papadopoulos and Milanović, 2017). Constraint with SSA, TSA majority function are risks early warning, classification and trend analyses. In the past two decades, researchers have conducted extensive explorations machine learning algorithms for the TSA of power systems, such as artificial neural networks (Sobajic and Pao, 1989), decision trees (Liu et al., 2014) and SVM (Echeverría et al., 2017).

Decision trees, SVM algorithm and improved classification algorithms are applied in TSA model, such as adaptive ensemble decision-tree algorithm (He et al., 2013), random forest algorithm (Negnevitsky et al., 2015), weighted random forest algorithm (Zhang et al., 2016), proximity driven streaming random forest algorithm (Zhukov et al., 2018). On-line TSA models transient stability margin has been classified by core vector machine (Wang et al., 2016b), and SVM incremental learning (Zhang et al., 2015). Post-fault transient stability condition has been predicted by a weighted SVM (Arefi and Chowdhury, 2017).

With wide-area measurement technology rapidly in recent years, numerous novel deep learning algorithms have been applied into the TSA of power systems (Zhou et al., 2018; Rueda-Torres and González-Longatt, 2018). TSA models building by deep learning could early warning and trend analyses of security risks. The key to the security assessment of power systems is the mapping relationship between system status feature and security stability (Wehenkel et al., 1994). For example, deep belief networks based on deep learning have been applied to the state classification of transient stability prediction (Zhang et al., 2018b) and the state classification of power systems fault (Zheng et al., 2017). A TSA model has been established by extracting and training the original input features by stacked auto-encoders and conventional neural networks (CNNs) algorithm (Tan et al., 2017), which dynamically displays transient process of power systems (Hou et al., 2018).

As shown in Fig. 4 (Xu et al., 2018): the overall framework of on-line security assessment comply with the stability requirements, establish situational awareness model, and complete the security warning classification; for the features extraction of wide-area data, the machine learning algorithms are applied to simulation calculation, analysis, and induction; and the trend analyzes of security are then completed (Yu et al., 2018); the on-line security assessment based on the actual applications of on-line dynamic warning and comprehensive defense; and an automatic information interaction system for multi-control center collaborative decisions is build (Vu and Turitsyn, 2017).

4.4. Applications of machine learning in smart dispatch

Aiming at the multiple time-scale problems of smart dispatch, some researchers studied the dispatching of 15 min level, such as the mechanism of flexible loads interactive response dispatching based on multi-agent systems (Palensky and Dietrich, 2011) and the micro-grid energy management optimal dispatching scheme (Pipattanasomporn et al.,

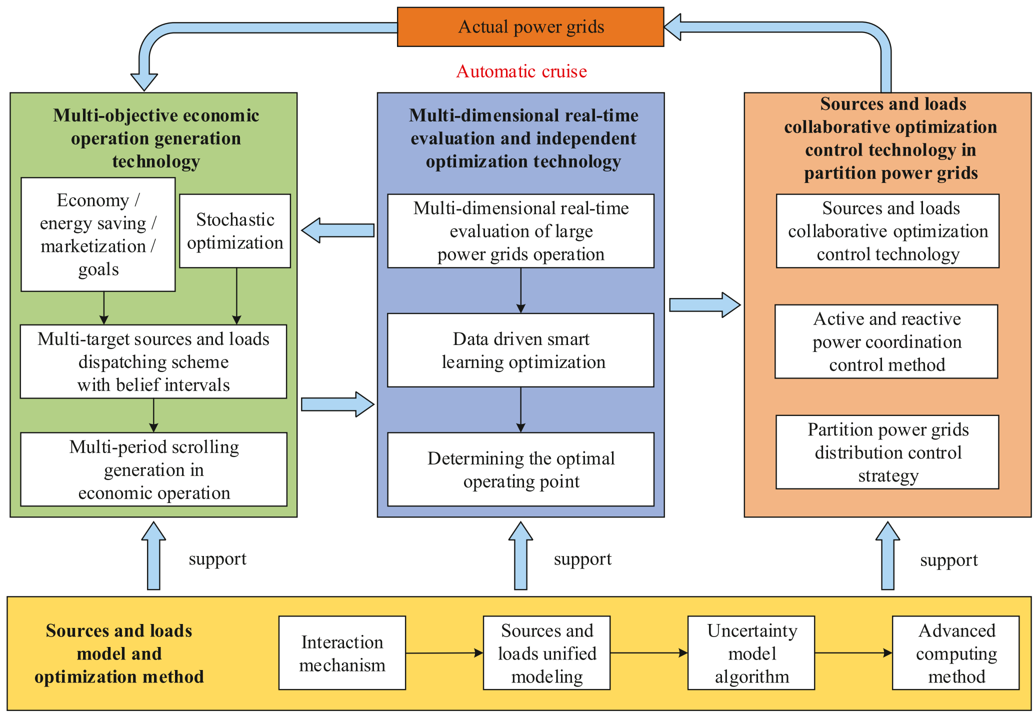

Fig. 3. Smart grid operation of optimal power flow.

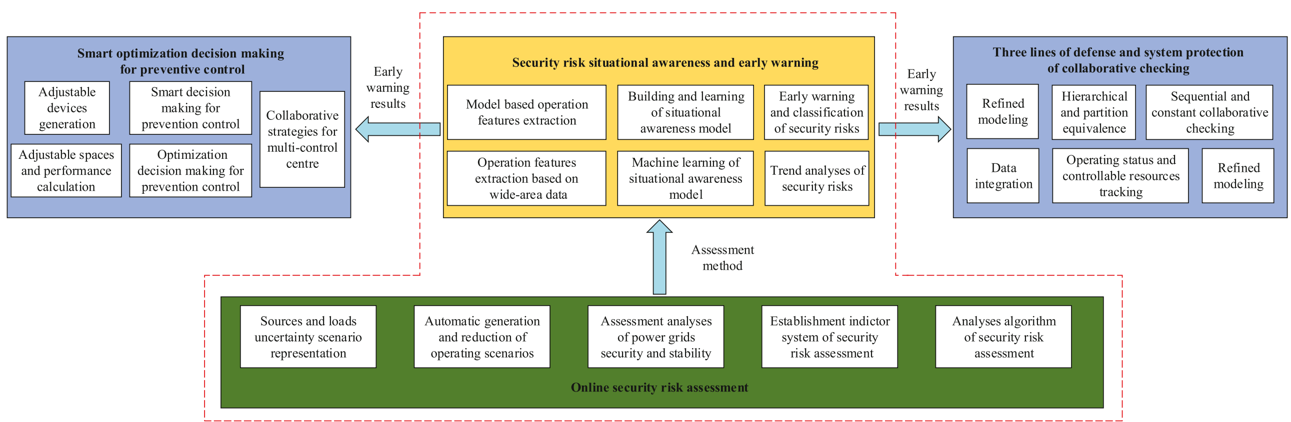

Fig. 4. On-line security risk assessment of smart grids.

2009); real-time dispatching with 5 min time-scale, renewable energy sources optimization dispatching based on model predictive control (Liu et al., 2015) and optimal dispatching of active distribution networks (Zhao et al., 2016); even to the second-level dispatching, real-time dispatching of 10 s for large-scale wind power (Khanabadi et al., 2018). The current smart dispatch that are predicted based on historical data (e.g. climate and weather data) and real-time power flow, that are coupling to multiple time-scale, and that are existing some deficiencies. Algorithms without a uniform time-scale will consider multiple time-scale in generation dispatch (1 day for unit combination problems, 4 h for economic dispatch problems, and 4 s for automatic generation control) (Pourmousavi et al., 2015).

As shown in Fig. 5, the total objective of smart dispatch is “automatic cruising in normal operation state and automatic navigation in abnormal operation state” (Fan, 2016). The strategy of smart dispatch is situational awareness. The operation trajectories of smart grids is fully described in the basic system of smart dispatch. The power-cyber–physical fusion technology, wide-area measurement technology, numerical prediction technology, and smart grids analysis and control technology are applied in smart grids (Kabalci, 2016). Besides, multi-domain information fusion, massive data mining, and smart grids situation prediction are employed in smart dispatch. Then, complete trajectory information and real-time extraction evolution characteristics of smart grids operation are obtained in smart dispatch. Finally, corrected and advanced control are achieved by on-line risk assessment and early warning in smart grids.

5. Dispatching robot technology framework and challenges based on group machine parallel learning

Parallel systems, which consist of actual systems and virtual artificial systems, have been proposed by Feiyue Wang at 2004 (Li et al., 2017b). The virtual artificial systems of parallel systems have been created to solve the problems of complex systems, and could control the controlled objectives in the case where the model cannot be established (Wang, 2010a). Therefore, parallel systems can be managed and controlled by the ACP theoretical systems (artificial societies, computational experiments and parallel executions) (Wang, 2007). The systems of parallel operating could be understood by parallel worlds or multiple worlds. The multiple feasible parallel solutions or Pareto optimal

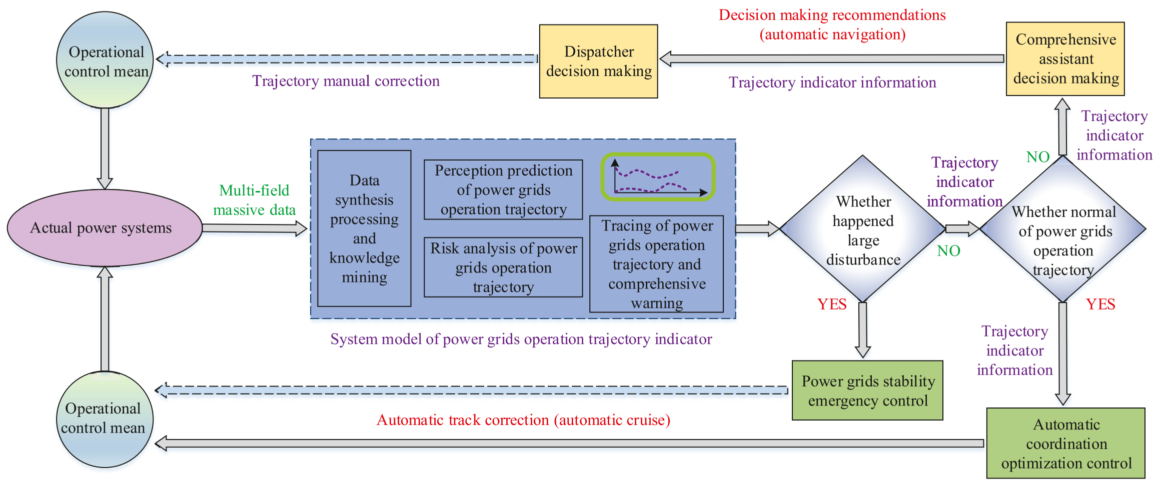

Fig. 5. Operation principle of smart dispatch.

Table 1
Development of parallel age.

Time	Development
1800 s	Mechanized age, Accusation 1.0
1900 s	Electrification age, Accusation 2.0
1950 s	Information age, Accusation 3.0
1980 s	Network age, Accusation 4.0
2010 s	Parallel age, Accusation 5.0, Age based on ACP theory and CPSSs

solution sets have been given by parallel worlds. The parallel systems and current parallel age 5.0 are based on ACP theoretical systems (Li et al., 2017b), such as industry 5.0 (Wang et al., 2018a), intelligence 5.0 (Özdemir and Hekim, 2018), control 5.0 (Wang, 2016), complex socio-economic systems (Wang, 2004), dynamic netizen groups (Wang et al., 2007), urban passengers transportation hub systems (Zhang et al., 2011), fear spread under terrorist incident (Chen and Zeng, 2004), unconventional emergencies (Chen and Xu, 2006), artificial environments (Wang and Tang, 2004), and the parallel systems of urban rail transit (Wang et al., 2016c). To ensure the stability requirements, power systems should explore more feasible solutions, search more solution spaces, and need to introduce parallel power systems.

The development trend of the parallel age (e.g. accusation age) is given in Table 1.

The CPSs in power systems are new development direction for large and even super large systems at nowadays. The CPSs are highly unified systems of networked physical devices with controllability, creditability, and extendibility (Lee, 2015); the CPSs combine technologies at the three levels, i.e., communication, control, and computing (Cheng et al., 2019); the modules of data collection, data processing, and communication are embedded into the physical systems, then the CPSs realize real-time interaction between physics and information systems through a secure, reliable and collaborative human-machine interfaces (Lee et al., 2015). The essence of CPSs is the fusion of physics and information, which conforms the basic physical laws (Tsoukalas and Gao, 2008). The CPSs include nature, environment, physics, electricity, society, economy, etc. Behl et al. (2016). Smart grids based on instructive CPSs could access various form of renewable energy sources (Yu and Xue, 2016). Meanwhile, cyber–physical–social systems (CPSSs) have been researched from the CPSs (Wang, 2010b).

The framework of CPSSs is similar to the ACP theoretical framework. Yusheng Xue, who is the academician of *The State Grid Electric Power Research Institute* in China, proposed "CPSs+" that combined CPSs with social factors (e.g. information security, adaptive decision-making, market mechanism, investment behavior, crisis management, game behavior, social behavior, government policies, natural disasters, emissions and environmental protection) (Rajkumar et al., 2010). The energy problem of "CPSs+" could be called CPESs, i.e., cyber–physical energy systems. Although the naming scheme is different, "CPSs+" is intrinsically consistent with CPSSs. Therefore, the tendency of power systems considering various factors, especially social factors, are inevitable tendency (Jiang et al., 2016).

The big data of smart grids are high-dimensional time-varying nonlinear data with multi-domain, different stability, multiple time scales, multiple physical quantities, and multiple spatial scales. The essence of smart grids is understood by big data ideas and extended cyber–physical power systems, which is CPESs (Wang et al., 2019). Then research on the big data and mathematical models have unique value and should not be replaced by each other (Ilic et al., 2008). Therefore, the applications of deep learning algorithms are studied in smart grids, which combine the big data with mathematical models to obtain stronger smart grids (He et al., 2017).

Game behavior (game theory) is common phenomenon in various social scenes. Game behavior exists in everywhere of life, every debate, every competition, even the bidding among businessmen, the balance of politics, economy and society, the diplomacy among countries, etc. Talebpour et al. (2015). The game is verified to maximize the interests of contradictory subjects under certain rules (Harsanyi and Selten, 1988). The game is divided into complete information game and incomplete information game, which could not obtain all the information of the game process. Incomplete information game has been applied in economic, social, national defense and other fields (Goeree and Holt, 1999). Furthermore, incomplete information game research has profound implications for decision-making support systems in all areas of society.

The dispatching structure of power systems will change in the future (Mediwaththe et al., 2016). For example, the dispatching structure based on the open power markets could be different from the current dispatching structure (Ghorbani, 2016). The decentralized power trading platform will be generated under the mechanism of open power markets, and thus the dispatching mechanism will become decentralized AlphaGo dispatching mechanism based on multi-group the game theory framework (Wen et al., 2018). In the future, the smart dispatching mechanism is flexible in the game theory framework, AlphaGo dispatching could be learned without the knowledge database, and AlphaGo dispatching with completely self-learning will be born (Zhang et al., 2018).

AlphaGo is distributed dispatching algorithm for incomplete information and cooperative game (Wang et al., 2016a). Dispatching AlphaGo requires the support of powerful computer hardware and efficient algorithms. The data is not only derived from the information of the dispatching area and external area, but also the market behavior (Bai et al., 2015). The studies of market behavior include

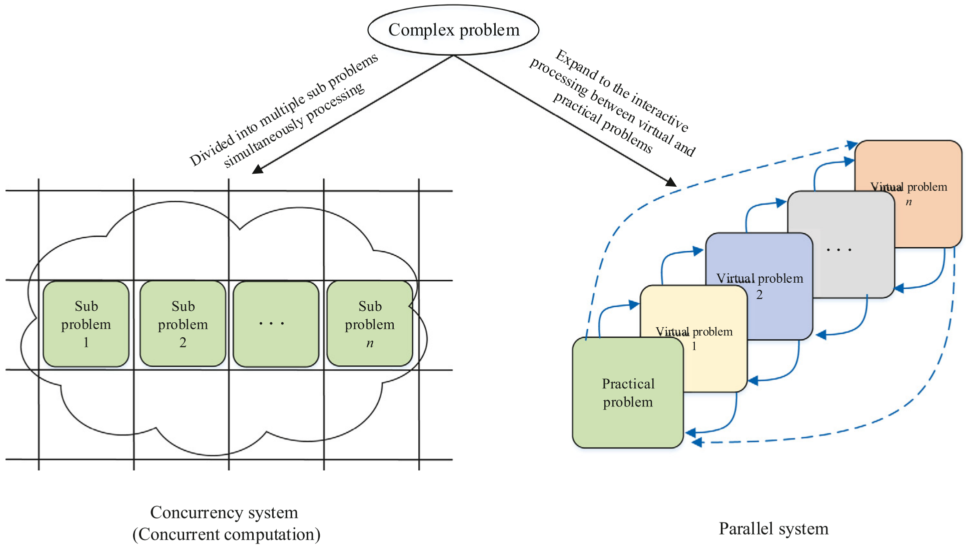

Fig. 6. Parallel systems.

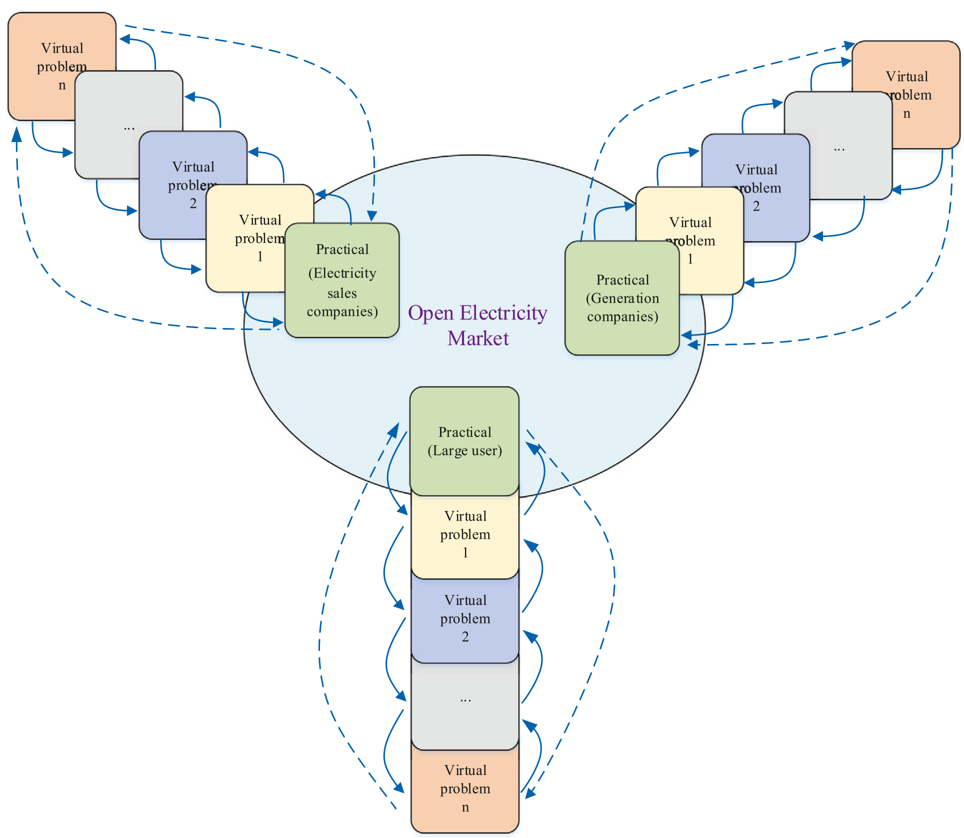

Fig. 7. Parallel systems based on multi-agent systems.

human systems, such as artificial investment behavior in the market, government-induced economic regulation and control behavior, human irrational behavior, and human emotional factors (He et al., 2018).

Therefore, the dispatching AlphaGo of the prediction of human behavior should be designed considering human behavior and game behavior (Capizzi et al., 2018). And unknown knowledge of the working conditions should be obtained considering the failures that have not occurred in the current stage (Li et al., 2019). Then fault knowledge of minimal probability will be obtained by constructing parallel systems, and the dispatching AlphaGo will explore the "swimming" of unknown knowledge.

The construction of parallel systems requires the construction of virtual systems, which correspond to the actual system. The building process of parallel systems is different from that of concurrent parallel computation, as shown in Fig. 6 (Wang et al., 2016c).

Thus, parallel systems of open power markets based on game behavior could be constructed as separate parallel systems for each game entity, as shown in Fig. 7.

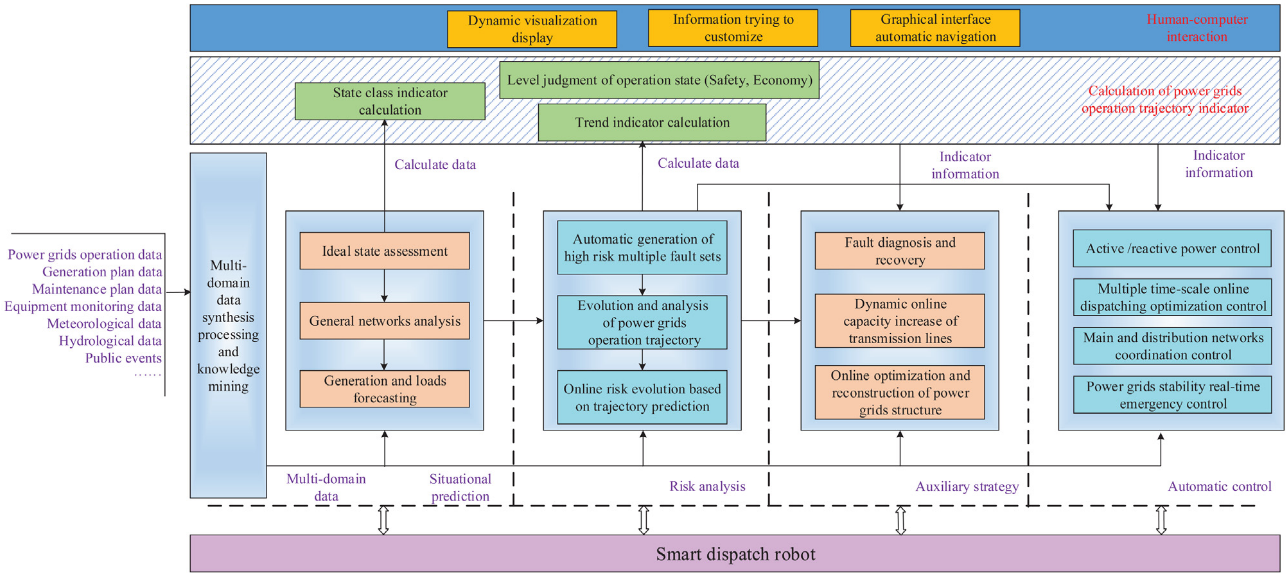

Fig. 8. Framework of dispatching robot technology based on group machine parallel learning.

Therefore, each entity selects dispatching strategy optimized by respective parallel systems, and continuously conducts dynamic games, even decentralized by Blockchain technology in the future open power markets (Sikorski et al., 2017). The framework of dispatching robot technology based on group machine parallel learning is show in Fig. 8 (Fan, 2016).

6. Conclusion

This paper analyzes the characteristics and challenges of new generation artificial intelligence dispatching system in power systems. Besides, this paper lists the applications of machine learning algorithms in smart dispatching and generation control, optimal power flow, security assessment. Then the dispatching robot technology and challenges based on group machine parallel learning are analyzed. Machine learning has been applied in numerous fields of smart grids researches. Overall, the applications are still in the primary research stage, which is still huge challenges in reliability, robustness and accuracy. In the background of artificial intelligence 2.0, industry 5.0 systems and cyber–physical energy systems, machine learning is undoubtedly a famous researched tendency in the future.

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