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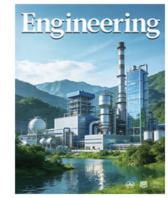

Research
Low Carbon Transformation for Conventional Energies—Review

Critical Review of Intelligent Coal-Fired Power Technologies and Applications

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ABSTRACT

With the rapid expansion of renewable energy systems, particularly wind and solar energy, coal-fired power plants (CFPPs) are expected to serve as flexible and dispatchable backup resources. This evolving role imposes new demands on their operational adaptability, efficiency, and intelligence. In this context, the intelligent transformation of CFPPs has become a key enabler for achieving both flexible operations and long-term sustainability. This paper provides a comprehensive review of the latest developments in intelligent coal-fired power technologies, focusing on three critical pillars: intelligent perception, intelligent control, and intelligent operation. Key enabling technologies, such as ubiquitous sensing systems, advanced control algorithms, and automated operation platforms, are examined in detail. Additionally, two representative engineering cases are introduced to demonstrate practical applications and benefits: the intelligent control of coal-fired units coupled with novel energy-storage systems and the implementation of unmanned operation in smart power plants. These projects highlight the transformative potential of intelligent technologies in enhancing the flexibility, efficiency, and autonomy of coal-fired power units. Finally, future perspectives on intelligent technologies are presented. The findings of this study offer valuable insights into the pathway toward clean, flexible, and intelligent coal-based power generation in an evolving energy landscape.

1. Introduction

Establishing a new energy system to achieve carbon neutrality is a key goal for society worldwide [1]. The vigorous development of renewable energy generation is a key initiative for building new energy systems, and the installation of renewable energy has increased rapidly over the past decade [2]. For example, in 2024, China added 79.82 GW of wind power capacity and 278 GW of solar power capacity, reflecting the continued strong growth in renewable energy development. In addition, China has added 373 GW of newly installed renewable energy power generation capacity, marking a year-on-year increase of 23%. Renewable energy accounts for 86% of the total newly installed power generation capacity nationwide [3]. Renewable energy, which is characterized by intermittency, randomness, and volatility, presents significant challenges in ensuring the safety and stability of the energy supply when integrated at high proportions. Furthermore, the widespread integration of diverse devices across the generation, distribution, and consumption sectors through power electronic interfaces has introduced new stability concerns in modern power systems [4]. The high penetration of power electronic devices has exacerbated these challenges, manifesting as nonlinear, time-varying, heterogeneous, uncertain, and complex system behaviors [5].

As the largest energy producer and consumer, China, driven by its goals of "carbon peaking and carbon neutrality," has introduced a series of policies [6–10] to promote the transformation of the energy system comprehensively. Among these measures, the construction of a new power system with new energy sources as a mainstay is a pivotal initiative. It aims to increase the proportion of new energy sources in the energy mix and enhance the cleanliness and sustainability of the energy supply. Continuous efforts to improve the flexibility of retrofitting coal-fired power have also attracted significant interest. This not only fully utilizes existing

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coal-fired power resources but also enables them to accommodate the integration of new energy better, thereby ensuring the stable operation of the power system. Collectively, these policies constitute a critical strategic framework for China's energy transition. In this context, coal-fired power plants (CFPPs) must transition from their traditional role as primary power sources to supportive and regulatory power sources [11]. As stable power sources, CFPPs would frequently operate under conditions that deviate from the design conditions to help the grid absorb more renewable energy from new energy systems [12]. However, the unit may suffer from a series of problems such as low power efficiency, insufficient peak-shaving ability, a decrease in device lifespan, and combustion instability [12,13]. Consequently, the intelligent transformation of CFPPs plays a pivotal role in advancing the energy transition and achieving sustainable development. Its primary significance lies in improving operational efficiency, enhancing flexible regulation capabilities, reducing operation and maintenance costs, minimizing environmental impacts, and ensuring safety and reliability.

Currently, research on intelligent coal-fired power technology primarily focuses on the following two aspects: first, operational parameter optimization based on big data and artificial intelligence (AI), leveraging real-time monitoring and data analysis to enable self-optimization and intelligent control of power units, thereby enhancing flexibility in addressing fluctuating loads and renewable energy integration; second, the development of integrated management and control platforms, incorporating intelligent sensors and actuators to improve operational stability and control precision [14–16].

Intelligent coal-fired power technology is an intelligent operation technology of CFPPs based on the foundations of automation, digitalization, and informatization, leveraging resources, such as the Internet and big data, to fully utilize the superior information-processing capabilities of computers. It integrates a unified data platform, unified management and control systems, intelligent sensing and execution, intelligent control and optimization algorithms, data mining, and refined management decision making. This approach establishes an intelligent operational control and management model characterized by self-optimization, self-learning, self-recovery, self-adaptation, and self-organization [15]. This transformation provides robust support for constructing an efficient, clean, and flexible new energy system, and has gradually attracted the interest of scientific researchers. In the context of digitalization, the intelligentization of CFPPs further establishes a solid foundation for the long-term economic viability and sustainable development of power plants. With the rapid development of renewable energy over the past few years, an increasing number of scholars have realized the significance of improving the intelligentization of CFPPs and have conducted various studies. Nevertheless, to the best of our knowledge, no one has summarized the latest research progress and technologies related to intelligent coal-fired power technology.

This paper presents an up-to-date comprehensive review of the research and development of intelligent coal-fired power technology, including intelligent perception, intelligent control, and intelligent operation. Furthermore, two CFPP intelligent transformation projects in which our research team participated are presented. This review provides a valuable reference for the intelligentization of CFPPs.

2. Characteristics of intelligent coal-fired power technology

2.1. Intelligent perception

Through developing intelligent sensing and implementing new technologies, the operation and maintenance of new coal-fired units can be effectively optimized, and the adaptability and control levels of automatic control systems can be improved. Currently, research on intelligent sensing primarily involves parameter detection, soft-sensing technology, and online coal quality analysis.

Parameter detection encounters challenges such as low data acquisition rates, a mismatch between the collected information and channel capacity, and insufficient levels of intelligence. The development of new sensor and high-speed communication technologies, such as fifth-generation mobile communication technology (5G) and wireless fidelity (Wi-Fi) 6, offers solutions to these problems. Intelligent devices that support chip-level sensing have been widely adopted [17]. Computational architectures such as edge and fog computing [18] have emerged rapidly.

Soft-sensing technology involves the collection of easily measurable variables to construct indirect variables representing the characteristics of complex control objects. Existing soft-sensing modeling methods can be divided into data-driven [19,20] and traditional mechanism-based [21] modeling methods. Soft sensing is achieved using traditional modeling methods by applying fundamental theories such as chemical reaction kinetics, material balance, and energy balance [21]. Data-driven soft-sensing technology primarily applies statistical methods and AI techniques to soft sensing [22].

The commonly used online coal quality analysis technologies include X-ray fluorescence (XRF), near-infrared spectroscopy (NIR), microwave (MW) spectroscopy, and laser-induced breakdown spectroscopy (LIBS). LIBS technology offers advantages, such as comprehensive measurement indicators, remote measurement capability, and no radiation hazards, making it highly promising in the field of online coal quality analysis. Companies in Israel [23] and the United States [24] have developed various measurement devices for coal based on LIBS. Although LIBS offers significant advantages in practical applications, the precision of the quantitative measurements requires improvement because of the instability of the plasma generated by laser ablation and the complexity of its spatiotemporal evolution mechanisms [25].

By developing ubiquitous sensing technology and fully using the mobile Internet, advanced communication technology and new sensing equipment can enable the comprehensive sensing of power plant status. This is useful for breaking through data barriers among people, machines, objects, and the environment, and realizing real-time data analysis. This section focuses on new ubiquitous sensing technologies from two perspectives: the composition of ubiquitous sensing systems and the applications of ubiquitous sensing technologies.

2.1.1. Ubiquitous sensing system

A ubiquitous sensing system for CFPPs is a set of monitoring systems for the entire plant equipment constructed using measuring and sensing technologies. It is composed of sensing, transmission, storage, and other equipment, as well as data acquisition and analysis tools and other subsystems. The system uses an intelligent sensing device installed in the equipment or the field operation environment to comprehensively monitor and perceive information, such as the equipment operation state and external environmental factors, and obtain multisource ubiquitous sensing data [15]. Using data transmission security protection technologies such as local area networks, security encryption, and access authentication, the ubiquitous sensing system transmits data to the real-time database of the entire plant, constructs a method of ubiquitous sensing data transmission and access network, and forms a three-dimensional monitoring system for the whole plant. This provides a reliable data basis for remote diagnosis, fault alarm, intelligent early warning, and condition maintenance of equipment, and comprehensively improves the perspective and perception ability of intelligent coal-fired power technology control systems at the production site [26].

As shown in Fig. 1, the network architecture of a ubiquitous sensing system in a power plant comprises sensing devices, communication networks, and servers. Sensing devices are used to collect critical data on power plant equipment and production operating environments. Data are transmitted through the corresponding communication network and ultimately consolidated on servers for unified management, analysis, and value-added utilization.

Sensing devices are the cornerstones of ubiquitous sensing systems. The system leverages advanced information technologies such as cloud computing, big data, Internet of Things (IoT), mobile internet, AI, blockchain, and edge computing [27] to mine, process, and analyze monitoring and identification data from various sensing devices in power plants. This facilitates real-time monitoring of operational management and supports decision-making based on this information. Sensing devices primarily consist of two categories: sensors and video-monitoring equipment.

(1) Sensors. The main equipment, such as turbines and boilers, is typically equipped with dedicated sensing systems that transmit status data to the ubiquitous sensing system database via data interfaces. These data serve as an information source for fault warnings and health management of the main equipment. However, the built-in monitoring systems of these units often fail to satisfy the growing demand for real-time sensing. This issue can be addressed by deploying appropriate sensor devices for the various sensing sources to achieve comprehensive condition monitoring. Various new types of sensors collect a broader range of real-time data across a plant, enabling the ubiquitous sensing of the plant's production and operation.

As shown in Fig. 2, intelligent sensing devices have higher performance requirements owing to the complex environments of thermal power plants, such as high-temperature conditions, dusty environments, high-frequency vibrations, and high-humidity conditions. Numerous acoustic, vibration, and pressure sensors have

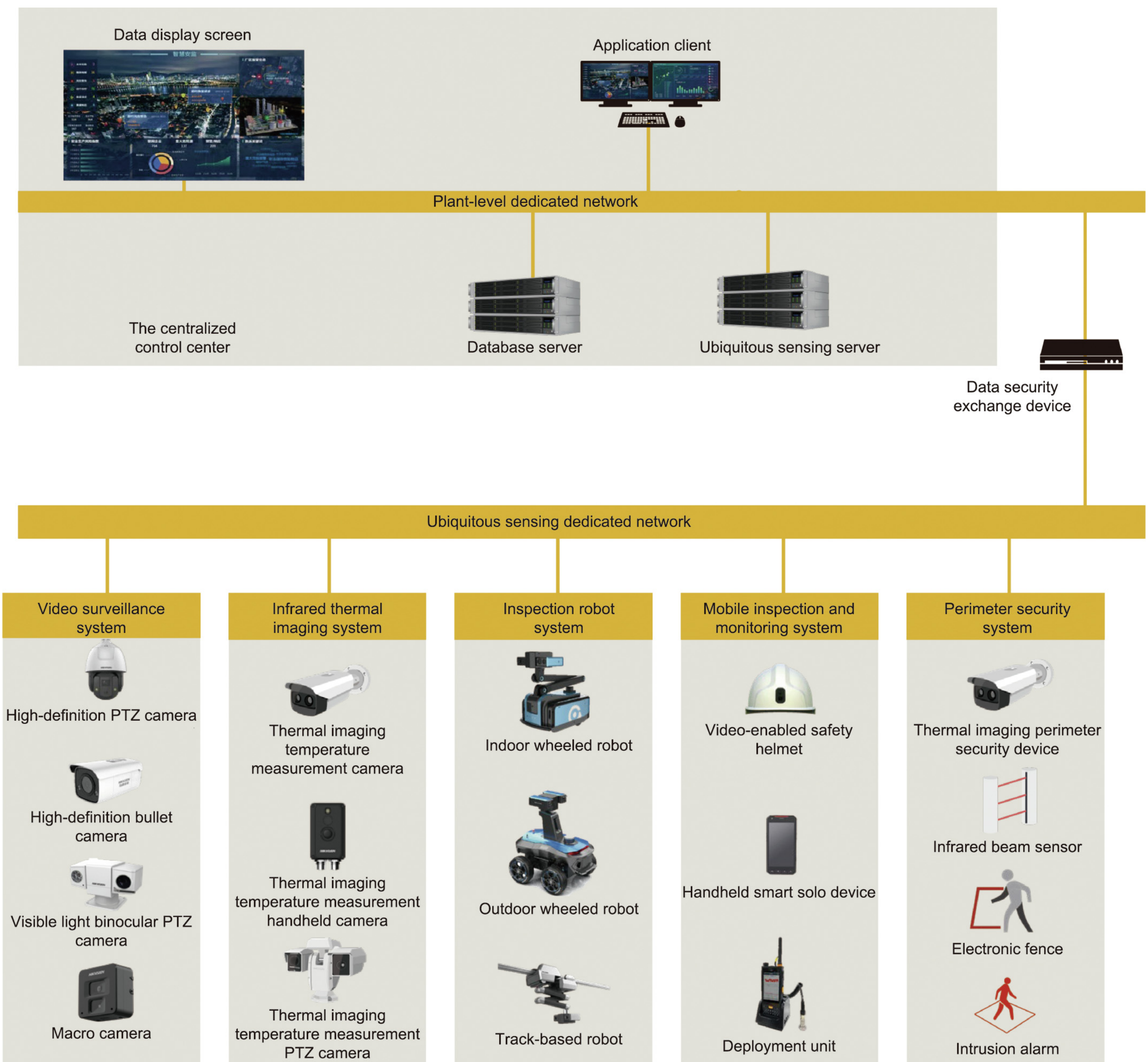

Fig. 1. Network architecture from ubiquitous sensing devices to a centralized control center in CFPPs. PTZ: pan–tilt–zoom.

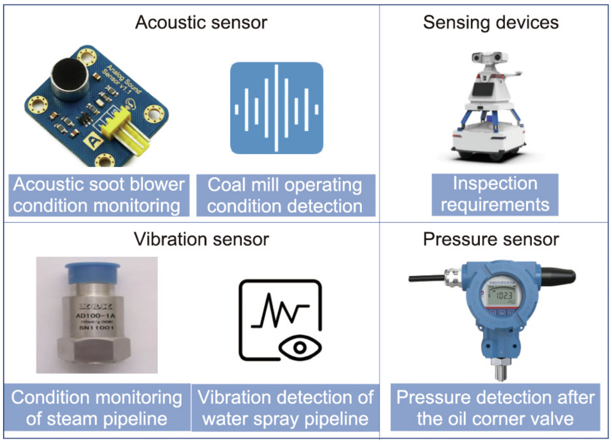

Fig. 2. Typical sensing devices for addressing detection challenges in power plants.

been deployed in various auxiliary equipment. Perception devices, such as inspection robots, are configured to satisfy diverse monitoring requirements. For intelligent sensing requirements of thermal power units (TPUs) to be satisfied, online detection devices for parameters such as coal quality [28] and the boiler temperature field [29] should be developed. Currently, advanced sensor technologies primarily include impact pulse perception recognition and flexible sensing technologies.

Vibration monitoring can monitor the magnitude and trend of the vibration of bearings and other equipment and aid in analyzing the causes of vibration. However, traditional vibration monitoring technology can only be used when an equipment fault is evident, and determining the severity of the equipment fault is difficult, resulting in misdiagnosis and missed diagnosis. Impact pulse technology can overcome the speed limit and measure the bearing state in the speed range of 1–20 000 $r\cdot min^{-1}$. Moreover, the vibration information of the bearing can be separated from complex background noise, the extracted data can be enhanced, and the correlation can be determined to obtain comprehensive, clear, and accurate bearing state information. Monitoring equipment for impact pulse technology has achieved remarkable results in early fault detection, which solves the problem of traditional vibration monitoring methods being unable to monitor low-speed equipment.

With the development of intelligent robots and wearable flexible electronic devices, flexible sensing technologies have become widely used. A flexible sensor is created from flexible materials that have good flexibility and ductility and can be bent or even folded freely. Its substrate is primarily composed of polyester, polyimide, and other materials, and its structures are flexible and diverse. Depending on the specific detection equipment or environmental conditions, different detection principles can be adopted to design the signal conversion mode to achieve rapid and accurate detection of special environments and signals in power plants and solve the problems of miniaturization and integration of sensors. However, many technical problems in flexible sensors remain: Currently, the preparation technology of materials used for flexible sensors, such as carbon nanotubes and graphene, is not mature, and problems such as cost, application scope, and service life remain [30]. Sensor substrates still have limitations such as poor resistance to high temperatures, resulting in high stress and weak adhesion between flexible substrates and thin-film materials. Furthermore, the assembly, alignment, integration, and packaging technologies for flexible sensors require further enhancement. Overcoming these challenges will improve the efficiency and capability of state detection in the complex environments of power plants.

(2) Video monitoring equipment. At some monitoring points, sensor devices alone cannot satisfy the requirements for condition monitoring. With the advancement of machine vision, non-intrusive intelligent recognition, and edge computing technologies [31], new camera devices can be utilized to perform intelligent analyses of real-time videos in conjunction with operational data (e.g., video-based personnel management). This enables capabilities such as equipment identification (e.g., video-based meter reading and indicator light recognition), hazard risk analysis (e.g., safety behavior recognition), remote control confirmation (e.g., switch status recognition), and abnormal condition detection. For example, several research teams have deployed intelligent edge-detection cameras equipped with power-AI dedicated video chips in the critical zones of CFPPs. These devices can perform on-site data decoding and transmit processed information to the central data center to verify anomaly alerts, thereby enabling real-time monitoring of equipment defects such as corrosion and cracks within the plant. Within a plant, mobile robots equipped with cameras and fixed video sensing and sensor devices can collaboratively monitor and identify the appearance of major equipment, instrument readings, and the open/closed status of disconnected switches.

2.1.2. Typical application of ubiquitous sensing

Currently, ubiquitous sensing technologies, such as soft sensing, online coal quality detection, and online monitoring of low-load combustion stability, have been validated in numerous coal-fired units, demonstrating promising application results.

(1) Soft-sensing technology. This new soft-sensing technology provides a rich and accurate perception method for optimizing the monitoring and control of TPUs. As shown in Fig. 3, based on the mechanism, it is primarily divided into two categories: traditional soft-sensing technology, which is constantly improved by relying on the progress of the mechanism method, and soft-sensing technology based on data or data–mechanism-driven methods.

Soft-sensing technology based on advanced TPU process theory is constantly improved by the progress of the mechanism method. By improving the cognitive level of complex control object characteristics, the leading variable factors are mined to achieve the correlation between soft-sensing variables and the production process. This type of soft-sensing object is often used in boiler combustion [19,32,33] and pollutant generation and removal processes [33]. In contrast to the direct parameter detection of several variables, a soft-sensing object can comprehensively characterize the production state of the unit and support the control, optimization, and decision-making of the main production process of TPUs from multiple dimensions and scales. Zhang et al. [32] conducted an in-depth analysis of the ultra-large inertia and multivariable coupling characteristics of circulating fluidized bed (CFB) boilers and developed a burning carbon model to represent heat storage in a CFB furnace. This enabled the dynamic modeling and rapid load variation control of CFB units. Zhang et al. [33] applied a soft-sensing model for "active limestone" to develop an SO_2 emission prediction model and established an optimized $n(Ca)/n(S)$ ratio method, achieving optimized SO_2 control for CFB units.

The second category is soft-sensing technology driven by data or a combination of data and mechanisms. Data-driven soft-sensing technology avoids the challenging process of accurately identifying mechanistic models but is constrained by factors such as the interpretability of "black-box" models. In contrast, the data-mechanism hybrid approach enhances the interpretability of purely data-driven methods [20]. This type of technology primarily targets the high-dimensional mapping of low-dimensional data in the production process of TPUs using state-space transformations to highlight certain characteristic variables. Currently, this

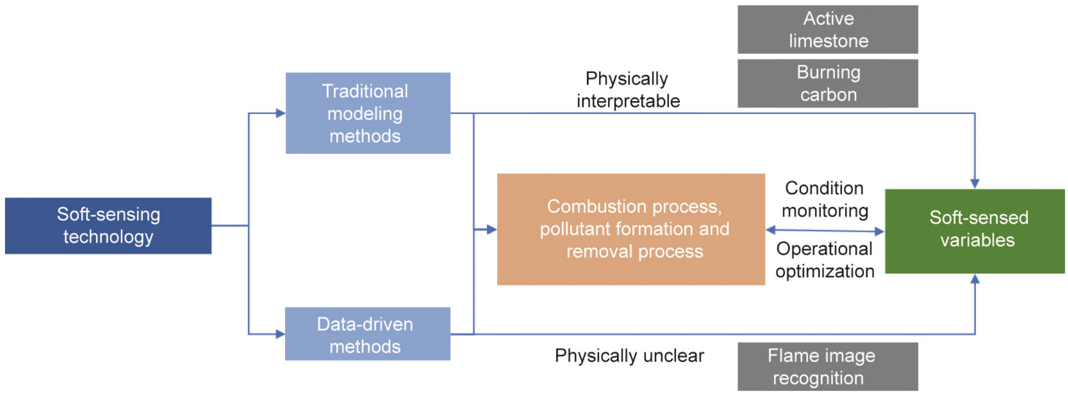

Fig. 3. Classification of new soft-sensing technologies.

type of technology has been applied in areas such as the combustion detection of TPUs based on flame images [34], flue gas oxygen content monitoring [35], and pollutant emission prediction [36]. Under flexible operating conditions, the complex operating states of power units impose certain limitations on the accuracy of soft-sensing models. A reasonable solution is to explore interpretable data-mechanism hybrid approaches.

(2) Online coal quality detection. In practical industrial applications, the matrix effects severely hinder the measurement accuracy and adaptability of online coal quality analyses. Current technologies generally mitigate the influence of matrix effects on detection results through data compensation. However, owing to the high complexity and strong nonlinearity of the matrix effects, data compensation often fails to achieve ideal outcomes. Song et al. [37] proposed a method for directly reducing matrix effects by dynamically adjusting parameters such as the laser energy and delay time in real time based on the actual temperature of the plasma. This approach ensures that the plasma temperature, electron density, and other characteristic parameters remain as consistent as possible across different coal types, thereby significantly reducing the impact of matrix effects, simplifying the quantitative model, and improving the measurement accuracy and coal adaptability.

Although LIBS technology for online coal quality analysis has advanced significantly and has been demonstrated in practical applications, further fundamental and applied research is required:

Interaction mechanisms. The interaction mechanisms among the lasers, coal, plasma, and environmental gases must be investigated. The influence of matrix effects, such as volatile matter and ash in coal, on plasma characteristics and spectral signals must be studied.

Plasma regulation. Based on techniques such as beam shaping [38] and spatial confinement [39], plasma regulation methods must be explored further to establish a stable spatiotemporal plasma window, thereby generating more deterministic spectral signals.

Quantitative analysis algorithms. Advanced quantitative analysis algorithms by integrating spectral processing techniques [40,41] with statistical, machine learning, and AI methods [42], must be developed. The physical context of LIBS coal quality analysis should be incorporated into the models to continuously improve the measurement accuracy and coal adaptability.

Industrial application. In industrial applications, the focus should be on measurement representativeness and long-term equipment stability to achieve stable, long-term measurements while reducing the maintenance workload.

(3) Online monitoring of low-load combustion stability. In the process of deep peak regulation, problems exist with the stability of boiler combustion [43]; therefore, an online system for monitoring the combustion stability of pulverized coal burners under medium- and low-load operating conditions should be developed [44]. Compared with contact and offline flame-monitoring methods, the online flame-monitoring method does not interfere with the measurement site and can reflect the combustion state of the fuel in real time [45,46]. As shown in Fig. 4, this system consists of two main components: a front-end hardware acquisition system and a back-end data processing system.

The front-end hardware acquisition system monitors and collects real-time data on the measurable parameters directly related to combustion, including visible light (flame images), infrared signals (flame detection), acoustic signals, and pressure. The back-end data processing system defines the quantitative combustion stability indicators corresponding to different experimental conditions through combustion adjustment experiments conducted on a single burner using a pilot-scale combustion test rig. A multimodal deep-learning regression model is then established to reflect the combustion stability of the individual burners. For better accuracy of the combustion stability detection under actual boiler combustion conditions, a transfer-learning model can be applied to generalize and extend the combustion stability model developed for the combustion test rig.

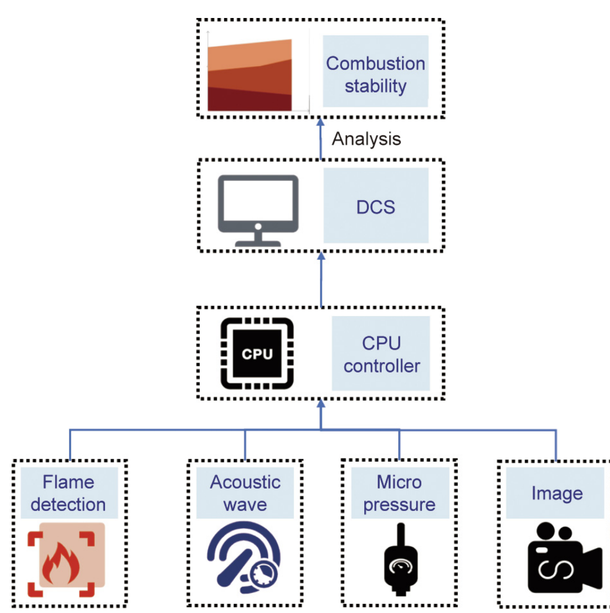

Fig. 4. Low-load combustion stability monitoring system. DCS: distributed control system; CPU: central processing unit.

A computational fluid dynamics (CFD) model is developed based on the mechanisms of pulverized coal flow combustion to enhance the theoretical depth and interpretability of the pulverized coal combustion stability. The model simulates the entire combustion process of pulverized coal particles carried into a furnace using primary air. By simulating the spatiotemporal evolution of the temperature, velocity, and chemical composition during the complete combustion of pulverized coal under different boundary conditions, the internal mechanisms underlying the changes in combustion stability were explored.

2.2. Intelligent control

A gap remains between the load change rate and minimum load of existing power units in China and the world's advanced level, and the support and regulation capabilities must be further improved [26]. Currently, coal-fired power generation units comprise three principal constituents: the boiler, turbine, and generator. The boiler is the key factor restricting the load change rate. The main restricting factors are as follows:

(1) During rapid load changes, rapid variations in the temperature and pressure parameters of the working medium result in relatively large thermal and fatigue stresses in the thick-walled components, which affect the service life of the equipment.

(2) The response of the boiler pulverized coal feeding system fails to match the load change instructions, resulting in an overall lag in the response of the unit.

(3) The hydrodynamic instability caused by the conversion between the dry and wet states of the boiler intensifies, posing a challenge to the safe operation of the power unit.

Current research on enhancing the flexibility of coal-fired units primarily focuses on the retrofitting of existing units. Although certain advancements have been achieved, formidable challenges persist in terms of the flexibility of retrofitting these units. Examples of such challenges include restricted economic efficiency and potentially adverse impacts on operational services. Research on coordinated control can be divided into two main areas: the modeling of transient process characteristics and the optimization of operational control.

(1) Transient process characteristic modeling of typical coal-fired generating units. The transient process characteristic modeling of typical coal-fired generating units can be categorized based on the functional roles of the various components. These include coal pulverizing, combustion, fluid compression and transportation, heat exchange, and heat-work conversion systems. These categories include coal-pulverizing, boiler, steam turbine, and cold-end systems [47]. Various modeling approaches, including mechanistic, data-driven, and hybrid models, are commonly employed in this area of research.

(2) Operation optimization control strategies. Operation optimization control strategies typically involve traditional control methods such as proportional–integral–derivative (PID) feedback and feed-forward control [48]. Additionally, the state-space equation is often employed to model the system and its processes. Advanced control techniques, including direct energy balance control [49], internal model control [50], predictive control [51], active disturbance rejection control [52], and nonlinear control [53] have been utilized to enhance control performance. The application of intelligent algorithms has become increasingly prevalent for improving existing methods and optimizing overall control strategies [54].

Traditional coal-fired units, which lack thermal energy-storage systems, typically rely on the coordinated control between the boiler and turbine. Therefore, new coal-fired generation units that integrate external energy storage systems should be developed. However, the integration of an energy-storage system raises questions regarding operational modes and instruction decomposition [55], which require further investigation.

2.2.1. Coordinated control of boiler–turbine–thermal energy-storage systems

Energy-storage systems coupled with coal-fired power generation are crucial for cooperating with the three major components (boiler, turbine, and generator) and improving the flexibility of power units. By storing energy in coupled units and releasing it outward, the spatiotemporal limitations of energy transfer in traditional coal-fired power generation units can be overcome. Moreover, the integration of energy storage with new coal-fired units enables spatiotemporal complementarity and enhances the in-depth utilization of energy storage, thereby improving the load-changing rate. However, these advanced energy-storage coupling methods introduce significant differences in the structure and operational processes compared to typical thermal systems. Consequently, further research on the coordinated control of the new system is required, focusing on three key areas: dynamic modeling, energy-storage system control, and coordinated control.

(1) Modeling of boiler–turbine–thermal energy-storage systems. A dynamic model should be developed to reflect the operating characteristics of advanced units accurately. The integration of an energy-storage system alters the processes of the thermal system, breaking the rigid coupling between the boiler and steam turbine. A precise mathematical model that captures the key dynamic characteristics of an operation is fundamental for the design and optimization of control strategies. High-precision models require well-defined boundary conditions and a layered structure. For example, for molten-salt thermal energy storage, constructing a high-precision mathematical model involves first analyzing the operational mechanisms of the system. This includes modeling the key heat exchangers involved in the molten-salt heat-storage and heat-release processes and assessing the impact of these processes on the unit. Furthermore, a dynamic nonlinear model of a boiler–steam turbine–molten-salt thermal energy-storage system is developed, which serves as the basis for the control strategy design. A simulator was constructed for the new units to provide a validation platform for refining these control strategies.

(2) Energy-storage system control. Integrating energy-storage systems into flexible grids is critical to addressing the intermittency of renewable energy and enhancing grid resilience. Its advantages are manifested in three aspects: First, energy-storage systems can smooth fluctuations in wind and solar power generation. By shaving the peaks and filling the valleys, a real-time balance between power supply and demand is achieved, thereby improving the consumption rate of renewable energy. Second, energy-storage systems have second-level response capabilities and can provide ancillary services, such as frequency regulation and voltage support, significantly enhancing grid stability. Finally, as battery and thermal energy-storage costs continue to decline, their economic viability gradually emerges, and grid parity has been achieved in some application scenarios.

The integration of energy storage with new units introduces multiple operational modes, making the safe and efficient switching between these modes a critical consideration in energy-storage system control. Automatic mode switching is essential to ensuring the safe and optimal operation of energy-storage systems. For example, a molten-salt system operates in several modes, including heat-storage, heat-release, heat-tracing, and heat-preservation modes. In the full-process automatic control strategy for a molten-salt system, a seamless switching logic between the heat-storage and heat-preservation modes, as well as between the heat-release and heat-tracing modes, should be designed [56,57]. Moreover, the energy-storage system control must account for the operational strategies of each mode under fault conditions. At the control-strategy level, the independence of the energy-storage system should be prioritized to minimize its impact on the conventional unit during fault events, and the key output parameters of the energy-storage system should be stable [58].

(3) Coordinated control. A coordinated control strategy tailored to the characteristics of energy-storage coupling is essential. This strategy should first define the response characteristics and safety boundaries of each energy-storage system. Furthermore, the multiscale energy-storage distribution behavior manifested should be dissected by the unit under heterogeneous operating conditions, and a quantitative methodology for computing energy storage should be devised. Based on the real-time distribution of energy storage, the load-command decomposition mechanism for a new unit should be studied. This enables the allocation of power between the boiler and each energy-storage system, as shown in Fig. 5. Additionally, a coordinated control strategy should be designed to leverage the energy-storage distribution and its in-depth utilization. The flexibility of operation across all operating conditions can be enhanced by optimizing the interaction between the boiler and each energy-storage system.

2.2.2. Automatic plant start-up and shut-down system (APS) with self-optimization for units

In large-capacity and high-parameter unit plants, thermal automatic control systems, particularly automatic start–stop control and coordinated control, have significantly improved labor productivity and power quality. These systems have also effectively reduced power generation costs, enhanced working conditions, and provided a reliable foundation for the safety, efficiency, and environmental performance of large units. The APS functions as a comprehensive management and control system, facilitating the automatic start-up and shut-down operations throughout the entire unit process [59]. It integrates both the analog and switching quantity controls.

The equipment involved in APS execution is complex, with intricate and variable start–stop conditions. In practical scenarios, various adverse factors such as equipment failures and parameter fluctuations tend to occur frequently. Such occurrences invariably result in the disruption of the traditional APS sequence. Subsequently, this demands immediate manual intervention from operators and consequently perturbs the seamless execution of the automatic start–stop process. With the ongoing reforms in the spot market, frequent startup and shutdown operations have become more common [60]. Thus, the gap between the automation capabilities of traditional APS and the requirements for frequent start–stop operations, particularly for peak shaving, must be bridged.

To address this issue, a new generation of self-optimizing APS must be developed. This self-optimizing APS should evaluate the impact of potential equipment failures and parameter fluctuations on sequence execution, and enhance its fault tolerance through a multipath design. A comparison of these processes is shown in Fig. 6.

The path planning of the self-optimizing APS should encompass a wide range of equipment start–stop combinations and judgment criteria to maximize flexibility. Through automatic evaluation of process parameters and equipment status, function groups independently determine their start–stop paths and execution timings. Additionally, the execution sequence and process parameters for each function group are governed by the prevailing process conditions, ensuring a high level of adaptability to operational scenarios and enhancing execution efficiency.

The path planning of the self-optimizing APS exhibits the following characteristics:

(1) The dual-mainline design consists of two parallel control paths: one for unit-level sequential control (APS main sequential control) and the other for the intelligent autonomous function group. During the APS execution, the intelligent autonomous function group continuously monitors the relevant process conditions and autonomously determines the optimal timing for initiating actions. These two mainlines operate in parallel and their process conditions are interdependent, thereby enabling the simultaneous activation and parallel operation of multiple function groups.

(2) The process conditions dictate both the start–stop process and direction of the process flow. Each function-group process condition independently determines the specific flow. By altering these conditions, the execution sequence of the function groups and the overall process flow can be adjusted, enabling the system to adapt autonomously to varying operational scenarios and enhance flexibility.

(3) The APS control range offers greater flexibility. For example, when a function group is automatically set to an APS, it is integrated into the APS and activated based on its process conditions. Conversely, when a function group is set up in the APS manual, it exits the APS and bypasses its process conditions. In this case, the operator determines when to engage the function group or perform operations at the equipment level without disrupting the APS process, thereby enabling modular debugging.

(4) In the event of abnormal equipment status signals, a thorough evaluation of the relevant process parameters is conducted to determine the actual state, improve the fault tolerance, and minimize unnecessary process pauses or interruptions.

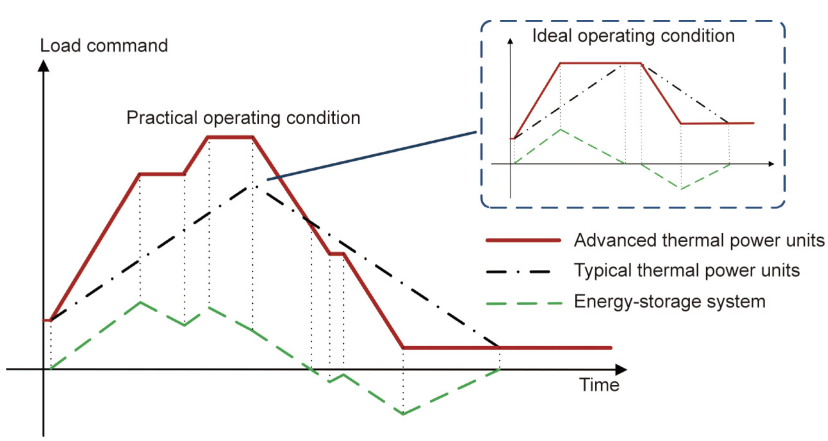

Fig. 5. Load-command decomposition for advanced TPUs with energy-storage system.

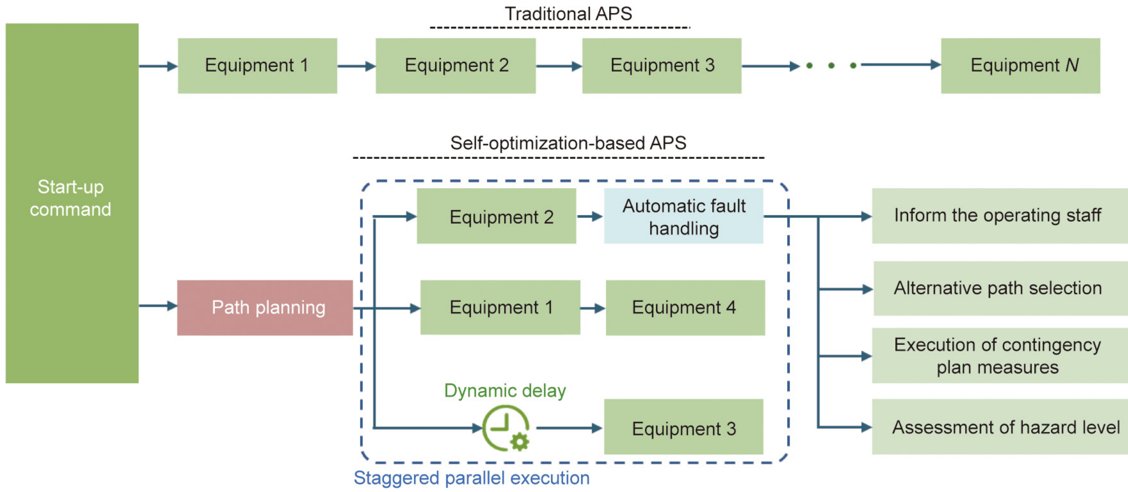

Fig. 6. Comparison of the processes between classical APS and self-optimization-based APS.

2.3. Intelligent operation

As the thermal power industry faces increasing demand for enhanced efficiency, reduced emissions, and improved operational reliability, the integration of intelligent technologies has become imperative. Current operational challenges, including the complexity of managing multienergy systems, the need for real-time optimization, and the necessity for proactive monitoring and maintenance, require a comprehensive approach to intelligent operations. To address these challenges, this section focuses on four key areas: establishing an intelligent control platform to enable automated and optimal management of power generation processes; implementing intelligent combustion techniques that optimize fuel usage and minimize emissions while ensuring system stability and safety; optimizing operations through intelligent algorithms to enhance energy efficiency and economic performance; and deploying advanced monitoring systems that provide real-time insights and early warnings to ensure the continuous and reliable operation of power plant equipment.

2.3.1. Intelligent control platform

By upgrading and expanding the computational capabilities and algorithms of controllers in conventional control systems, an intelligent control hardware platform is established. This platform supports functions such as intelligent monitoring, performance evaluation, advanced control, operational optimization, and multienergy scheduling, thereby enabling fully automated optimal control. This development significantly enhances the controllability and adjustability of the units, thereby improving operational efficiency and environmental performance.

The intelligent control platform, which is centered on an advanced distributed control system (DCS), simplifies the power generation information system architecture, forming a "two-layer structure" comprising intelligent control and intelligent management layers [15]. The intelligent control layer overcomes the limitation of unidirectional data flow, enabling operational guidance information to interact directly with the lower-level control loops. This interaction creates an "energy efficiency closed-loop" operation model that supports continuous self-optimization. The integration of advanced detection and sensing technologies, the IoT, 5G data access, and intelligent components such as dedicated data analysis networks, real-time data platforms, and intelligent computing engines strengthens the platform's capabilities in industrial data analysis, knowledge inference, process control, and proactive safety management. These capabilities enable comprehensive data analysis and value extraction by effectively applying advanced control theories and methods. The resulting intelligent operating platform is depicted in Fig. 7.

Intelligent control platforms provide significant improvements in operational flexibility and optimization capabilities. However, its novel architecture may require additional training of personnel, potentially limiting its immediate scalability.

2.3.2. Intelligent combustion

For self-adaptive combustion control across all operational conditions, intelligent combustion must not only address economic and environmental considerations but also ensure the stability and safety of the combustion system under varying operating conditions. The research focus has shifted toward optimizing combustion under low-load and variable operational scenarios. From a technological standpoint, this involves the integration of online detection, CFD simulations, statistical data analysis, and other advanced techniques. Utilizing online coal quality detection results as a critical input, the goal is to optimize boiler safety, stability, economic performance, and environmental outcomes across a range of operating conditions, including varying loads and coal qualities. The relevant technologies are shown in Fig. 8.

Intelligent combustion, which leverages both online and soft measurement technologies, incorporates machine learning and numerical simulation techniques to extract key combustion state

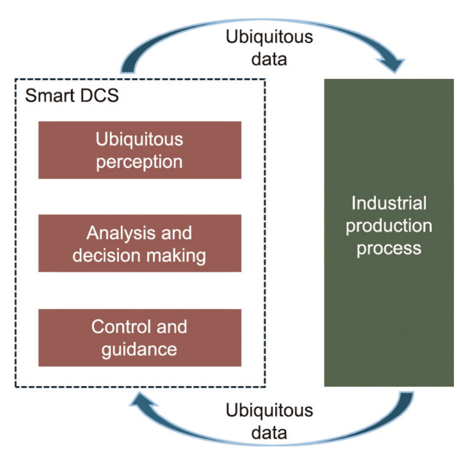

Fig. 7. Closed-loop operational architecture of the intelligent control platform based on a smart DCS.

features such as the flame center, temperature field distribution, and temperature gradients. This enhances the capability of comprehensive combustion state monitoring and analysis. A hybrid modeling approach that combines combustion mechanisms with data-driven insights is employed to establish the mapping relationship between the adjustable operational variables of the boiler and optimization objectives, including boiler efficiency, emissions, and coal ash slagging characteristics. This approach enables the real-time online modeling and optimization of the combustion process. Additionally, a combustion performance indicator system, built upon full-condition recognition, is developed to provide a quantitative assessment and multiobjective evaluation of the boiler's combustion safety, stability, economic performance, and environmental impact. By adopting a hierarchical control system structure, an integrated combustion control technology based on intelligent coordination and local optimization is established. This system incorporates both closed-loop and intelligent control strategies to enhance the overall combustion performance.

Intelligent combustion technology can enhance operational efficiency and contribute to emission reduction through real-time optimization and improved monitoring. Nonetheless, the reliance on complex models and high-quality data can pose implementation challenges and require substantial initial investment.

2.3.3. Intelligent optimized operation

Intelligent optimized operations primarily encompass economic analysis and operational optimization. Through performing online calculations of high-precision performance indicators, conducting new consumption difference analyses, and integrating advanced operational optimization technologies, the operational parameters or modes of coal-fired power units can be adjusted to enhance energy consumption efficiency and other related performance metrics.

(1) Online algorithms for high-precision performance indicators. Currently deployed online algorithms for performance indicators in power plants primarily use methods such as correlation parameter curve fitting or simplified calculations, such as basic thermal balance. Owing to design and testing condition limitations, these methods have poor accuracy and suffer from numerical drift, thus offering limited guidance for plant operations.

For improved accuracy of online indicator algorithms, customized calibration device models and their internal characteristic parameters can be developed through data aggregation, analyses, and field research. Enhanced calculation methods, such as parameter back calculation, curve correction, and online self-calibration, can be adopted to obtain real-time operational performance. In field implementation, the method shows an inverse correlation between power generation coal consumption and load variation, with real-time coal consumption calculations aligning well with the real-time coal supply.

(2) Novel consumption difference analysis. Existing consumption difference analysis functions mostly focus on calculating the consumption difference for major deviation items but have not achieved comprehensive consumption difference analysis and closed-loop consumption difference control. The novel consumption difference analysis targets key equipment, such as boilers, steam turbines, and generators, reflecting changes in boiler efficiency, steam turbine thermal consumption, and generator efficiency. Auxiliary machine performance deviations are reflected as changes in plant electricity usage. Deviations in the adjustable operating parameters on the furnace and machine sides are reflected in changes in the boiler efficiency and steam turbine thermal consumption, whereas deviations in the thermodynamic system parameters are reflected in changes in the steam turbine thermal consumption.

A comprehensive analysis of the consumption differences can be implemented based on this classification. Methods such as experimental calibration, equivalent enthalpy drop, and thermal balance analysis are used to obtain precise values for each consumption difference sub-item. The optimization adjustment sequence for each controllable consumption difference sub-item is accurately determined by comparing the criticality of each item. Combined with the high-precision performance indicator online algorithm mentioned earlier, real-time calculation of the precise values of the performance indicators is performed, which are compared with the theoretical optimal values to obtain the overall system consumption difference analysis value. By summing all sub-items and comparing the cumulative value with the overall system consumption difference analysis value, the difference is analyzed to achieve a closed-loop consumption difference analysis.

(3) Integrated operational optimization. To adapt to rapid load changes in units and the coordinated operation of the unit, boiler, and energy-storage system, the safety, stability, economy, and environmental performance indicators under different operating

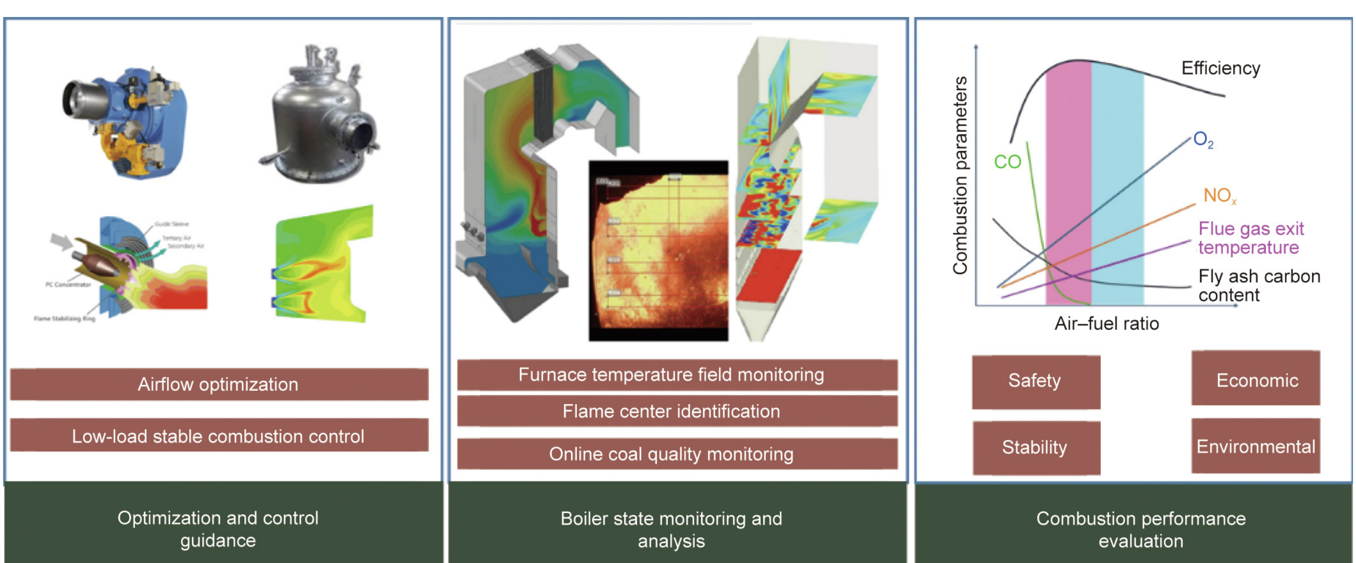

Fig. 8. Functional framework of intelligent combustion system: optimization, monitoring, and performance evaluation.

conditions must be balanced. This involves coordinating factors, such as energy consumption metrics, regulation requirements, safety constraints, dynamic deviations, and equipment performance, as shown in Fig. 9.

The operational differences under various conditions are shown in Fig. 10. A comprehensive optimization calculation model for all operating conditions is established, targeting the key controllable operational parameters of the unit. For these critical parameters, optimized operation recommendations and feedback control integration are provided, ensuring that the optimized values are used for control, thereby achieving a real-time optimization control loop with no human intervention or autonomous optimization.

An intelligent optimized operation enables a more accurate perception of the actual state of the unit, enhancing the economic performance through precise real-time adjustments and comprehensive analyses. However, integrating multiple optimization techniques and ensuring closed-loop control can present significant technical and operational challenges.

2.3.4. Intelligent monitoring

Intelligent monitoring aims for "minimal staffing and unmanned operation," relying on operational mechanisms and data as its foundation. By leveraging advanced technologies, such as big data and AI, and aligning them with the operational procedures and management requirements of thermal power plants, it monitors, provides early warnings, and evaluates the operation and status of power plant equipment. This ensures high-reliability state monitoring and early warning, fault diagnosis, and traceability, thereby providing reliable support for decision-making.

(1) Multisource heterogeneous information fusion monitoring model. An intelligent monitoring function should drive the exploration of higher-level intelligent applications, such as multisource heterogeneous information fusion. This involves structuring and modeling various types of information, including production data, operational procedures and experiences, maintenance documents and records, anomaly handling solutions, and audio–visual content. The goal is to build an integrated monitoring model, as shown in Fig. 11. Commonly used pre-trained models for text include generative pre-trained models (GPT) [61], ChatGLM [62,63], LLaMA3 [64], and Baichuan [65]. For audio, pre-trained models such as L3-net [66] and PANNs [67] are employed, whereas for video, pre-trained models such as VideoBERT [68], TVLT [69], and VATT [70] are utilized.

For monitoring targets, multimodal analyses and intelligent algorithms are used to promptly identify, warn, and diagnose potential risks, anomalies, and issues in TPUs. By leveraging mixed-reality technology that integrates virtual information with real-world scenarios, the perception and understanding of the environment and equipment by monitoring personnel can be enhanced. This approach improves situational awareness and enables more effective and proactive decision making during operations.

(2) Equipment-oriented mechanism-data evaluation and diagnosis. The development of health assessment, early fault warning, and fault diagnosis functions relies heavily on big data and AI technologies. These functions depend primarily on historical trends rather than on the intrinsic mechanisms of equipment operation. The integration of equipment mechanisms and correlation at the equipment level still requires to be enhanced to ensure that the diagnosis process not only uses data trends but also accounts for the underlying operational principles of the equipment.

A mechanism-data evaluation and diagnosis model is constructed for the key equipment within the boiler-storage system. Starting from the equipment structure and operation mechanisms, the model enhances the personalized evaluation and problem localization capabilities of different pieces of equipment based on common evaluation and diagnosis principles. Additionally, a knowledge graph provides a knowledge representation framework for coal-fired units that integrates massive multimodal information in a one-stop manner. It encapsulates expert knowledge such as operational experience, operating procedures, and anomaly handling solutions into diagnostic models.

The main process involves the construction of a knowledge graph, development of operational guidance models, creation of fault diagnosis models, generation of models driven by fault diagnosis models, and feedback and improvement in the evaluation process. Key entities within the unit-boiler-storage system, such as equipment, components, and processes, are identified. After determining the relationships between these entities, mapping and embedding are performed to generate a series of tokens. These tokens are used to fine-tune the operational guidance models. After fine-tuning, the models are driven by the fault diagnosis model, and the outputs may include the root cause of the fault, its impacts, and recommended repair steps. Finally, based on feedback from maintenance personnel, a self-learning and self-updating mechanism for the system is implemented, which reduces false positives and missed reports.

Intelligent monitoring systems can improve operational oversight and fault detection through advanced data integration and real-time diagnostics. However, the complexity of multisource data fusion and the need for continuous model updates pose challenges for implementation and maintenance.

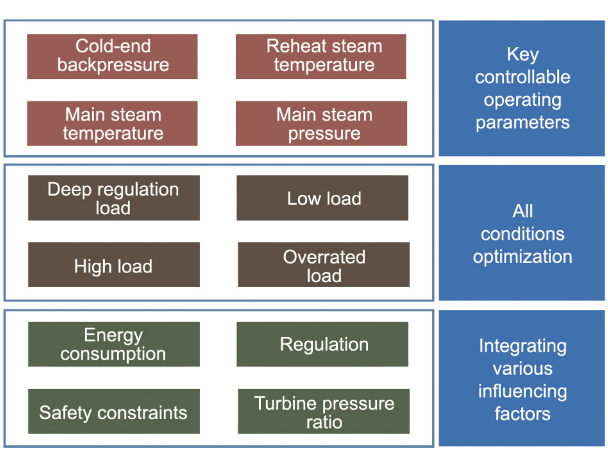

Fig. 9. Comprehensive optimization scheme for key parameters under various working conditions.

3. Two engineering cases for the intelligent coal-fired power technology

The coupling of energy-storage systems to enhance the flexibility and economic performance of coal-fired power units has become a key development trend in the future of coal power generation. The integration of energy-storage systems into conventional coal-fired units fundamentally alters their operational characteristics and poses new challenges for the intelligent management and control of such units. Furthermore, the implementation of optimized control logic, along with the adoption of intelligent technologies, such as one-click start/stop and autonomous decision-making, is considered a hallmark of next-generation unmanned CFPPs. Accordingly, this paper concludes by presenting two representative projects in which our research team was deeply involved: ① the integration and operation of a flywheel energy-storage system (FESS) at the Lingwu Power Plant

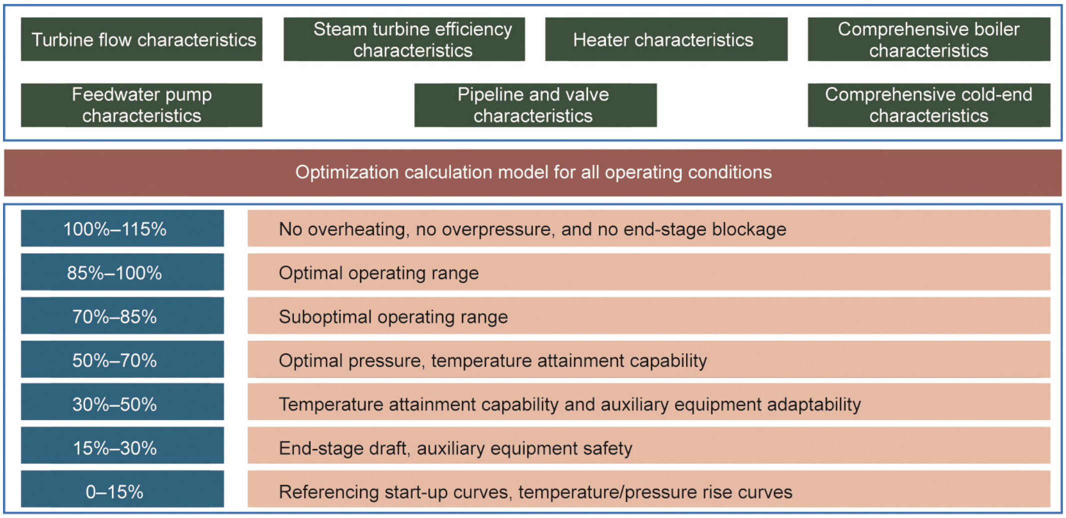

Fig. 10. Optimization of full working condition partitioning.

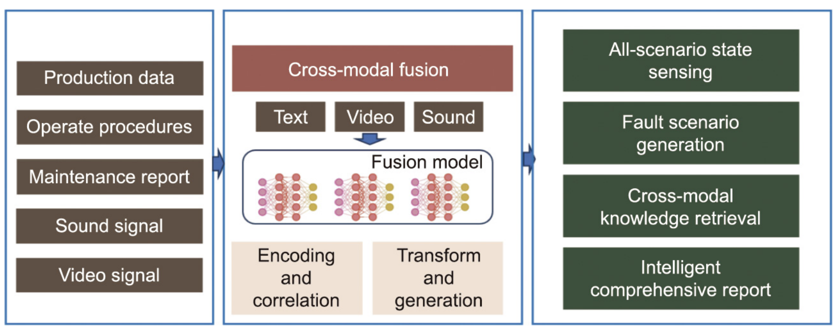

Fig. 11. Multisource heterogeneous information fusion supervisory model.

and ② the unmanned operation retrofit project at the Dingzhou Power Plant.

3.1. Flexible and intelligent control of flywheel energy storage and coal-fired power generation

Renewable energy sources, such as wind and solar power, are inherently random and intermittent, posing significant challenges to the frequency stability of China's power system when integrated on a large scale. In the context of new power systems, extensive grid integration of distributed energy sources such as wind and solar energy has sharply increased the demand for flexible regulation resources.

The rapid development of high-power FESS provides an effective solution to the problems of frequency security and power grid stability.

To alleviate the pressure of dispatching frequency regulation under the new power system structure, promote the consumption of new energy, and maintain the safety of the new power system, the first full-capacity "FESS + thermal power joint frequency regulation" project has been developed and built at the Ningxia Lingwu Power Plant of National Energy Co., Ltd. (China), which has the largest single energy-storage capacity in the world and the largest single power.

The project design and installation of 36 flywheels, which is shown in Fig. 12, comprises a single flywheel rated power of 500 kW, up to 630 kW, the total capacity of 22 MW$\cdot$(4.5 MW$\cdot$h)$^{-1}$, which made it the first full-capacity "FESS + thermal power joint frequency regulation" project in China's coal power field, and also the world's first 500 kW$\cdot$(125 kW$\cdot$h)$^{-1}$ level of engineering application flywheel.

With the coordinated control of the boiler–turbine–energy-storage systems, the qualified rate of primary frequency regulation of the unit increased by approximately 30% after the project was implemented.

This project has significantly improved key power quality indicators such as primary frequency regulation and automatic generation control (AGC) in the Lingwu Power Plant. Fig. 13 shows that when the FESS is not operated in the primary frequency regulation, the primary frequency regulation qualification rate of unit #2 of the Lingwu Power Plant is the lowest at 63.90%, the highest is 71.30%, and the average is only 67.42%. After the FESS began operation, the qualified rate of the primary frequency regulation significantly improved; the lowest qualified rate was 84.00%, the highest was 95.40%, and the average qualified rate was 88.68%. The participation of the fire-storage combined system in the primary frequency regulation was 21.26% higher than that of the original TPU.

With the FESS, the comprehensive K_p regulation performance index of the AGC frequency regulation improved by 16.4%. Table 1 shows the results of the influence of the FESS on the AGC frequency regulation performance index of the unit for one day. Under different AGC amplitude changes, the FESS can actively participate according to its state to achieve a fast response, advanced response, and timely compensation, as shown in Fig. 14.

In addition, after the TPU–FESS coupling AGC frequency regulation, the average daily power of the statistical FESS participating in AGC frequency regulation reaches 16.4 MW$\cdot$h, the qualified rate of

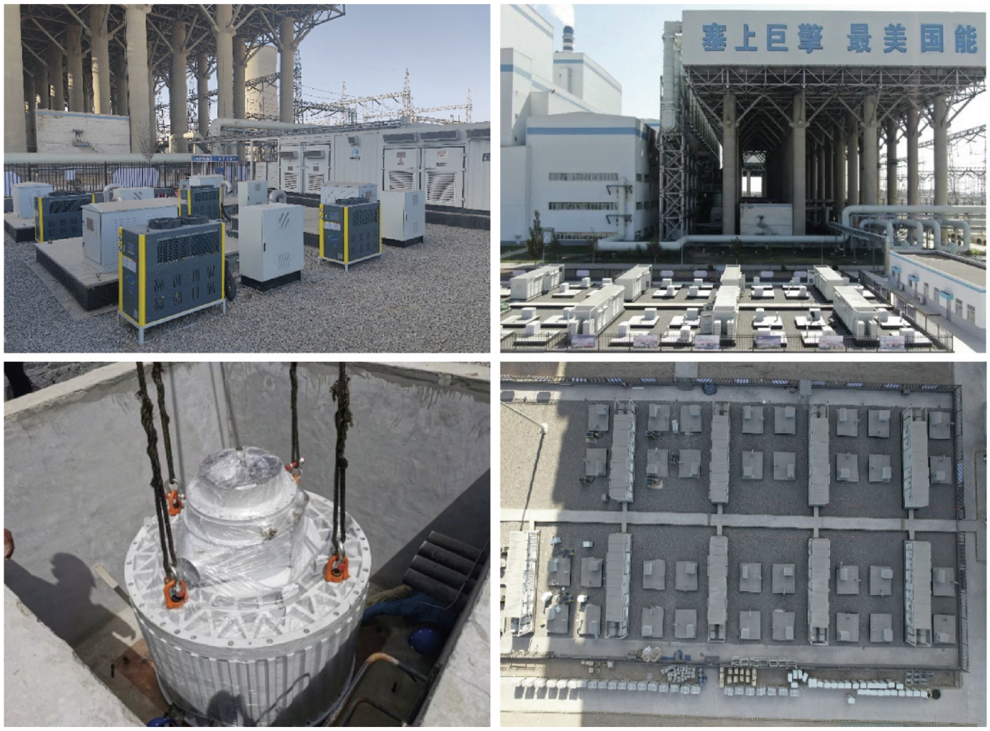

Fig. 12. Lingwu Power Plant maglev flywheel energy-storage project site.

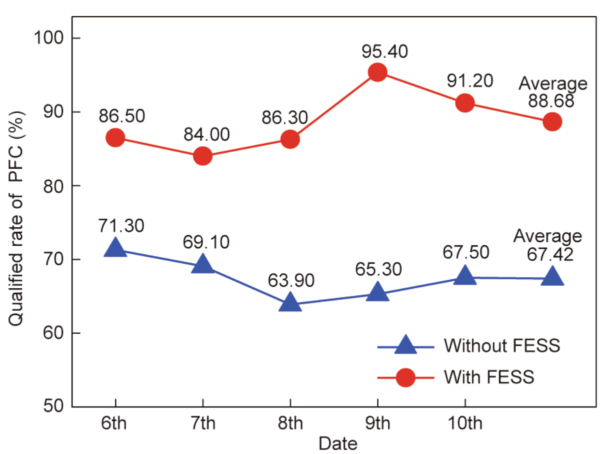

Fig. 13. Comparison of historical qualification rate data of unit #2 on the same date in October and November.

the contribution power can be increased by 20%–40%, and the monthly power integral can be increased by 295 points, which can increase part of the frequency regulation income for the power plant. Additionally, the participation of the FESS can effectively improve the AGC frequency regulation performance of the power plant. According to the statistical data of the power grid, the fire-storage coupling frequency regulation can reduce the assessment score by 142 points per month, correspondingly reducing the monthly assessment cost. Considering the auxiliary benefits of flywheel energy storage combined with the TPU frequency regulation and reduced assessment costs, the overall economic benefits of this project are evident.

The total annual income of the project can reach 35.148 million CNY, and good economic and social benefits have been achieved, which is a successful practice of FESS in the field of power.

As the first full-capacity TPU–FESS joint frequency regulation demonstration project in China, the Ningxia Lingwu Power Plant maglev FESS is composed of 36 630 kW flywheel energy-storage units in parallel, which can provide key technical support for the clean and efficient comprehensive utilization of coal and assist the consumption of new energy.

Through key technologies such as intelligent control, intelligent decision-making, and energy-storage system control, the project can provide power auxiliary services to support the safe and stable operation of large power grids, significantly improve the flexibility and economic benefits of traditional thermal power plants, and provide reliable technical support for the grid to significantly absorb new energy.

3.2. Dingzhou power plant adopts unattended whole-process intelligent control

In new power systems, coal-fired units face significant challenges such as changing external environments, complex operating conditions, and personnel reduction to increase efficiency. These challenges require higher adaptability, performance, and reliability for long-term continuous operation without manual intervention of related control systems. Taking the unattended control

Table 1
Analysis of the influence of flywheel energy storage on AGC frequency regulation performance index of the unit.

Energy storage configuration	Rate of regulation k_1	Response time k_2	Adjustment accuracy k_3	K_p
Not invested	1.09	0.75	0.49	0.902
Invested	1.29	0.77	0.61	1.050

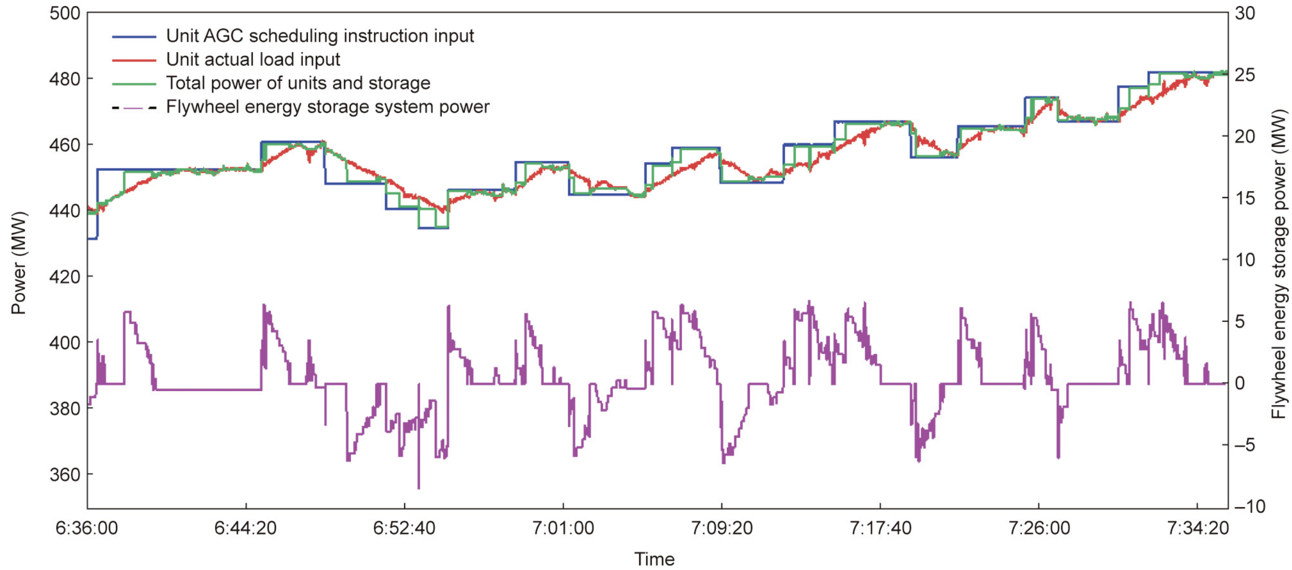

Fig. 14. Actual curve of the coupling system combined with AGC frequency regulation.

implemented in the Guoneng Dingzhou 600 MW subcritical unit as an example, this paper introduces the important role of autonomous control and autonomous decision technology in achieving the intelligent transformation of coal-fired units.

3.2.1. Application of autonomous control technology in the steam temperature control system

In response to frequent load changes, the fluctuations in any parameter in the boiler combustion system affect the steam temperature. For a steam temperature system with an apparently large delay and large inertia, the control system cannot perform the targeted compensation control designed for each disturbance, making conventional feedback regulation based on the cascade control strategy unable to meet the demands of steam temperature control quality under the new situation. Consequently, operators must frequently adjust certain machines to manually compensate for these disturbances.

Because of the complex characteristics of disturbances in steam temperature, establishing a corresponding control model is difficult. To address the frequent model changes of the steam temperature control channel under a wide range of load variances, a steam temperature whole-process autonomous control system based on the combination of front–feedforward–feedback structures was designed. A multistep prediction model based on transformer architecture was developed to forecast the steam temperature trajectory under variable load disturbances. The model takes the historical time-series data of the unit load, treatment of each layer, air distribution, and flow of attemperating water as inputs, which are encoded with positional embeddings. A multihead self-attention mechanism was employed to capture the long-range temporal dependencies and nonlinear coupling relationships. The model is trained on real plant data to minimize the mean squared error between predicted and actual steam temperatures. The predicted temperature trend is then used to soften the preset setpoint in advance, enabling a proactive intervention to mitigate the disturbance impacts. This neural network prediction model corresponds to the neural network model and extraction of steam temperature change feature modules in the left part of Fig. 15, which depicts the intelligent front-end feedforward control mechanism. As shown in Fig. 15, the overall system integrates intelligent sensing and the softening of preset values with adaptive feedback mechanisms. Moreover, given the regulation margin of the two-stage superheated desuperheating water and stepwise generalized predictive control as the core, a superheated steam temperature-segmented control strategy based on the temperature difference between the inlet and outlet of the desuperheater is proposed to overcome the internal disturbance of desuperheating water. Subsequently, an online model identification and update strategy is adopted to improve the adaptability under variable working conditions and enhance the whole-process autonomous control capability of the steam temperature system.

Fig. 16 shows the daily average statistics of the manual operation times during the commissioning process of the steam-temperature autonomous control system. The figure shows that, in the presence of the steam temperature autonomous control system, the operating quantities of the valves and set values related to the steam temperature system decrease significantly. When the intelligent control system is used for a longer period, the daily average manual operation quantity decreases by more than 98%.

Meanwhile, the steam temperature whole-process autonomous control system achieves a significant improvement in the control quality, as shown in Fig. 17. In the process of continuous load rise/drop and load fluctuation of the unit, intelligent distribution and scheduling of primary and secondary desuperheating water quantities are performed based on the predicted steam temperature. Consequently, the main steam temperature fluctuation is no more than ±5 °C under variable load conditions, which is superior to a dynamic deviation of no more than ±8 °C at the early stage of reconstruction.

3.2.2. Application of autonomous decision technology in optimized dispatching control of a coal pulverizing system

With the advent of new energy power systems, owing to frequent load changes, the coal pulverizing system must be frequently started and stopped. According to statistics, more than 30% of the daily operating quantity of a conventional power unit originates from the start and stop operations of the coal pulverizing system. The optimized scheduling control strategy for the coal pulverizing system based on the autonomous decision technology is shown in Fig. 18. It includes an autonomous dispatch center, autonomous decision control system, and function group combining mill preparation/start/stop/parallel withdrawal.

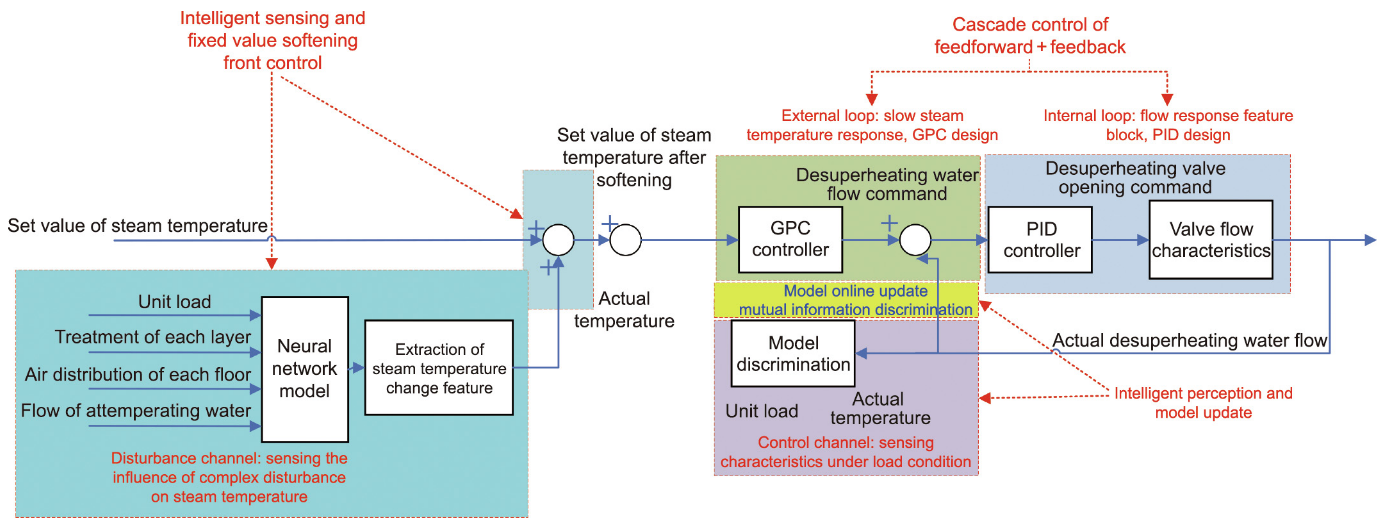

Fig. 15. Schematic of intelligent control of the steam temperature system. GPC: generalized predictive control.

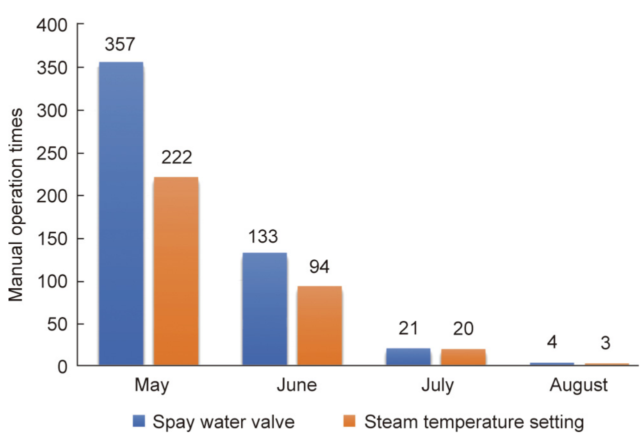

Fig. 16. Change trend of average daily manual intervention volume of the steam temperature control system.

(1) The autonomous dispatch center plans the optimal operation combination of different coal mills to achieve optimal boiler efficiency.

(2) The autonomous decision control system distinguishes the status of the coal pulverizing system according to the load condition of the unit and makes intelligent judgments according to the current operating conditions to complete automatic conversion between different working statuses of the coal pulverizing system.

(3) The function group combining mill preparation/start/stop/parallel withdrawal achieves automatic start, stop, standby mill preparation, and coal feeding/reduction without human intervention.

Fig. 19 shows the statistics of the average daily manual operation times during the commissioning process of the optimized scheduling control strategy of the coal pulverizing system. The figure shows that with the presence of this new system, the operation quantities of start–stop, standby mill preparation, and parallel withdrawal are significantly reduced. The average daily manual operation quantity is reduced by more than 96% after three months.

Fig. 20 demonstrates that the new system can independently optimize the mill combinations. When the load of the unit is stable, the temperature of the primary superheater is relatively high in the initial state, the desuperheating water valve is opened excessively, and the main steam temperature is relatively low. At approximately 210 s, an independent decision is made to stop mill E in the upper layer and start mill A in the lower layer. After the combination of mills is optimized, when the steam temperature of the primary superheater is basically unchanged, the opening degree of the primary desuperheating water valve is reduced from 60% to 40%, the main steam temperature is increased from 535 to 543 °C, and appropriate desuperheating water exists. While preventing the overtemperature risk of the primary superheater, an improvement in the main steam temperature improves the boiler efficiency.

Targeting the key controllable operating parameters of the unit, the application of autonomous decision-making and autonomous control technology provides a real-time optimized control loop with no human intervention and independent optimization, and achieves a breakthrough from conventional automation to highly independent operation of the unit; thus, the coal-fired unit has more efficient adaptability, higher reliability, and better economic operation capacity.

4. Future perspectives

In this era of rapid technological advancement, the future of power generation is poised to be reshaped by intelligent systems and innovative solutions. As traditional energy systems transition toward sustainability and efficiency, the integration of advanced technologies, such as AI, big data, and flexible operation mechanisms, will redefine the design, operation, and management of power plants. This evolution will not only enhance the operational performance of power generation units but also establish a new paradigm for intelligent, adaptive, and sustainable energy production. Future research should focus on the following aspects:

As a core enabler of intelligent transformation in CFPPs, ubiquitous sensing technology is transitioning from a proof-of-concept to large-scale deployment. Although novel solutions continue to emerge, challenges remain, including high retrofit costs and unresolved interference issues in complex operational scenarios. With the large-scale application of advanced communication technologies, new sensing technologies, and perception technologies in power plants, and by exploring their deep integration with AI methods and the operational mechanisms of power units, monitoring and recognition data can be mined, processed, and analyzed from various sensing devices in power plants. Furthermore, implementing modular designs and open-source protocols effectively

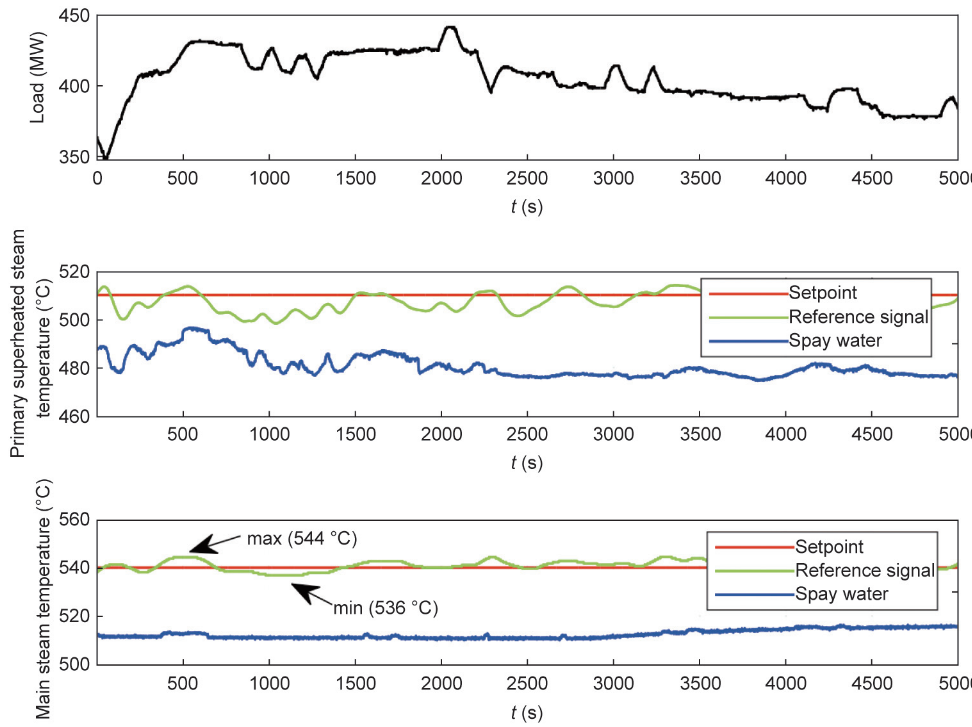

Fig. 17. Full-process autonomous control curve of the main steam temperature.

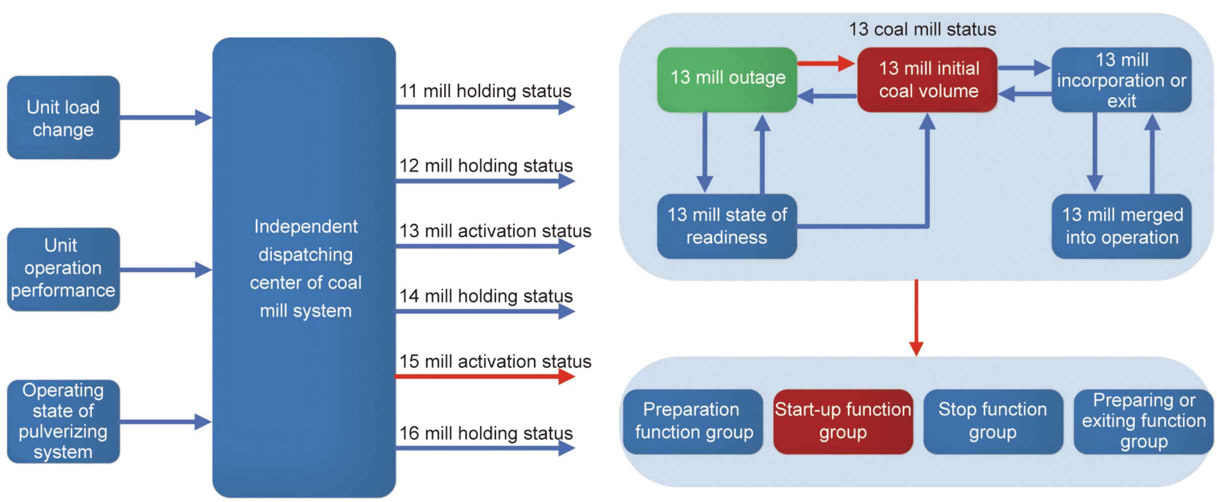

Fig. 18. Schematic of the intelligent decision making of coal pulverizing system.

reduces the deployment costs of ubiquitous sensing systems, ultimately yielding cost-efficient standardized solutions to facilitate large-scale adoption of the technology. This will enhance the comprehensive state awareness capability of power plants, provide a foundation for unmanned intelligent operation and intelligent control technologies, and further improve the digitalization and intelligentization levels of power plants, ultimately achieving the goals of intelligent management and control.

The flexible operation of coal-fired power generation units imposes practical demands on intelligentization, which provides essential technical support for achieving flexibility. The automatic control system is the core of this transformation. On one hand, the adoption of advanced flexibility technologies across boilers, turbines, generators, and energy-storage systems enhances a system's perception and execution capabilities. On the other hand, the integration of thermal energy storage necessitates a fundamental redesign of control strategies and operational modes. Building on automation and informatization, the development of intelligent control technologies, including intelligent sensing, control, optimization, and decision-making, offers a viable pathway for improving operational efficiency, adaptability, and maintenance quality. Future control frameworks should coordinate thermal units and energy-storage systems across multiple timescales to enable rapid load tracking while ensuring strict environmental compliance. Multiobjective optimization is critical for balancing cost efficiency, flexibility, and emissions reduction. Additionally, intelligent systems must evolve to incorporate market-aware mechanisms, such as dynamic bidding, ancillary service participation, and carbon pricing responses, to adapt to changing power markets. Key technical challenges remain, including the development of adaptive

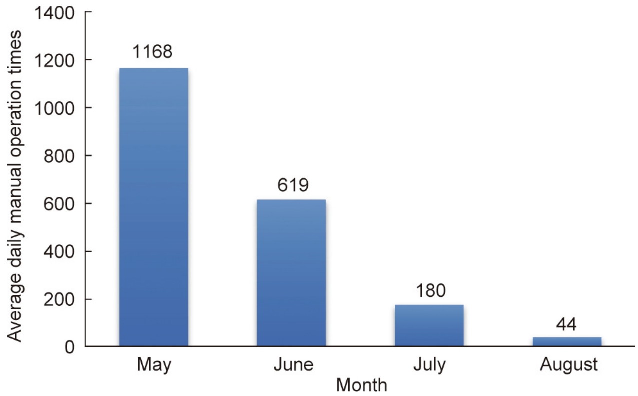

Fig. 19. Change trend of average daily intervention volume of the coal pulverizing system.

control models under uncertain conditions, ensuring real-time industrial data quality and security, and deploying edge intelligent systems for low-latency and high-reliability inferences. Improving the model interpretability and trust through hybrid learning approaches is vital for large-scale deployment. Addressing these issues will enable the coal-fired units to become highly flexible, clean, and intelligent assets for future low-carbon energy systems.

Intelligent operation in thermal power plants will increasingly emphasize unmanned operation and fully closed-loop control optimization. By leveraging large-scale AI and big data technologies, future systems are expected to achieve autonomous monitoring and decision-making, significantly reducing human intervention while enabling real-time process optimization to improve efficiency and reduce emissions. However, integrating AI-driven decision making into real-time operations poses several challenges that define important future research directions. These include ensuring high-quality, stable, real-time data acquisition under complex industrial conditions, developing adaptive and generalizable models that can cope with varying load patterns and unforeseen disturbances, and designing safe, standardized integration interfaces with existing DCS/programmable logic controller (PLC) systems. In addition, enhancing model interpretability and trust through hybrid learning frameworks and human-in-the-loop strategies is essential for safe deployment. From a methodological perspective, key future directions include the application of reinforcement learning for sequential decision-making, online learning for adaptive modeling under nonstationary conditions, edge AI deployment for low-latency inference, and multisource heterogeneous data fusion for comprehensive state awareness. Furthermore, research on the co-optimization of thermal systems and energy storage using AI-driven scheduling and control algorithms is crucial for achieving flexible and low-carbon operational objectives. Addressing these technical and methodological challenges is essential for building resilient, explainable, and practically deployable intelligent control platforms for coal-fired power-generation systems.

Currently, released energy policies have established a clear guiding path for the development of coal-fired power technology. Through the top-level design of carbon peaking and carbon neutrality goals, the coal-fired power industry has gradually changed from a traditional high-carbon emissions model to a clean, low-carbon, flexible, and efficient model. Under the guidance of these policies, future coal-fired power technologies will focus on breakthroughs in the following directions: deep peak-shaving and rapid response technologies. By means of stable combustion at low boiler loads, molten salt power generation, and flexible retrofitting of steam turbines, the regulatory capacity of the generating units can be enhanced. Second, near-zero emission and carbon capture technologies were used. Emphasis will be placed on the research and development of low-carbon technologies such as efficient combustion, flue gas purification, and carbon capture, utilization, and storage (CCUS). The third is intelligent operation and maintenance, as well as multienergy coordination technologies. Digital twins, AI, and other technologies can be applied to achieve intelligent operations. Fourth, there are cogeneration and comprehensive utilization technologies. Thus, the efficiency of energy cascade utilization will be improved. The policy orientation is promoting the transformation of coal-fired power from a single power-generation function to a multifaceted collaboration of electricity–heat–carbon. This enables it to gradually transition toward

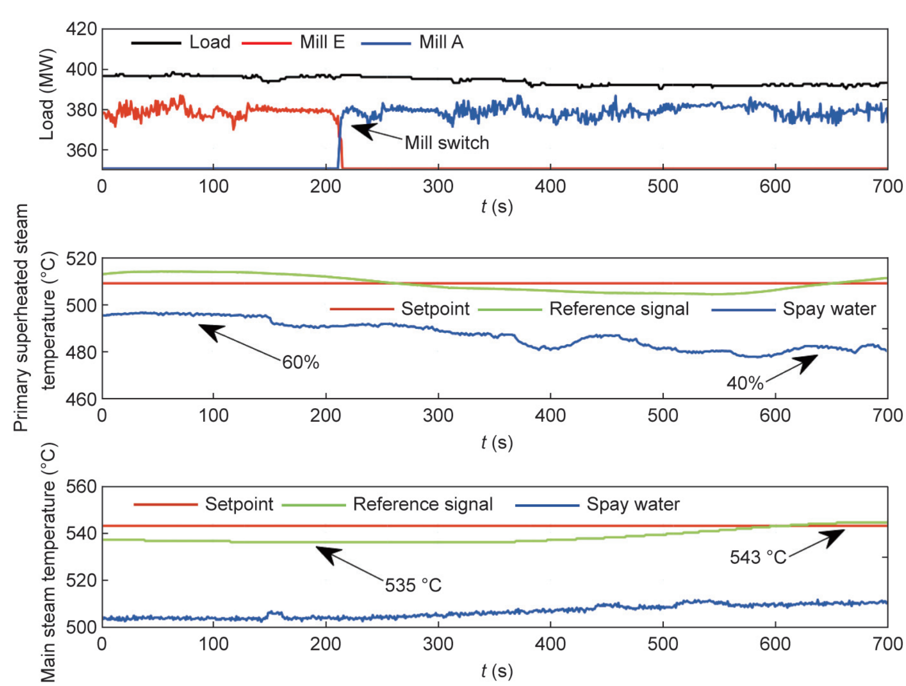

Fig. 20. Full-process autonomous decision control curve of the coal pulverizing system.

low-carbonization, intelligence, and integrated energy services while ensuring the flexibility of the power system, ultimately achieving in-depth integration and development with new energy sources. These technological breakthroughs will not only improve the environmental performance and operational efficiency of coal-fired power units but also reshape their strategic value in the new power system, providing crucial support for the green and low-carbon transformation of the energy sector.

5. Conclusions

CFPPs are undergoing a fundamental transformation from traditional base-load generators to highly flexible and intelligent system-supporting assets in response to the growing integration of renewable energy into modern power systems. This shift is driven by the urgent necessity to enhance load-following capabilities, reduce emissions, and improve the overall economic performance of conventional CFPPs. Against this backdrop, the intelligent transformation of CFPPs has emerged as a critical enabler of sustainable energy transitions.

This paper provides a comprehensive and up-to-date review of the key enabling technologies that underpin intelligent coal-fired power generation, focusing on three major dimensions: intelligent perception, intelligent control, and intelligent operation. In the area of intelligent perception, advancements in ubiquitous sensing systems and soft-sensing technologies have significantly improved the real-time observability and diagnostic capabilities of TPUs. Intelligent control strategies, such as the coordinated control of boiler–turbine–energy-storage systems and autonomous start–stop logic, have enabled more adaptive, reliable, and efficient operations, particularly under fluctuating grid conditions. Intelligent operation frameworks supported by integrated control platforms, machine learning models, and multisource information fusion technologies are reshaping the management of thermal power plants, transitioning from conventional automation to closed-loop, data-driven, and minimally staffed operations.

The two engineering cases presented in this paper—flywheel energy storage integration at the Lingwu Power Plant and unmanned control retrofit at the Dingzhou Power Plant—serve as representative examples of the practical application of intelligent technologies in large-scale coal-fired units. These cases demonstrate that by coupling with energy storage and deploying autonomous control and decision-making systems, significant improvements can be achieved in frequency regulation performance, operational reliability, and economic efficiency. Moreover, they exemplify the evolving paradigm of CFPPs toward higher intelligence, reduced human intervention, and increased compatibility with renewable energy.

Despite these promising advancements, several technical and engineering challenges must be overcome. These include the need for more robust and adaptive models for system perception under uncertain conditions, real-time decision-making frameworks that integrate with edge-computing platforms, and improved interpretability of data-driven algorithms for secure deployment in safety–critical environments. Additionally, multiobjective control frameworks must be developed to address operational flexibility, emissions reduction, cost-effectiveness, and market responsiveness simultaneously, particularly considering emerging carbon trading mechanisms and ancillary service markets.

Future research should continue to explore the synergistic integration of intelligent technologies, energy-storage systems, and flexible operational strategies. The development of standardized, modular, and scalable intelligent control platforms is key to enabling widespread deployment across different plant types and operating scenarios. With continued interdisciplinary collaboration and policy support, CFPPs can be repositioned as cleaner, more flexible, and digitally empowered assets in the low-carbon energy landscape. This review serves as a valuable reference for researchers and practitioners committed to accelerating the intelligentization of thermal power and achieving a more resilient and sustainable energy future.

CRediT authorship contribution statement

Jizhen Liu: Project administration, Conceptualization, Writing – review & editing, Funding acquisition, Supervision. **Zhongming Du:** Writing – review & editing, Conceptualization, Methodology, Formal analysis. **Qinghua Wang:** Writing – original draft, Conceptualization, Supervision. **Kaijun Jiang:** Writing – review & editing, Conceptualization. **Dan Gao:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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