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Review

Hydro–Wind–Photovoltaic Multi-Energy Centralized Control Systems and Digital Twin-Based Simulation Training Platforms: A Review

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Abstract

With the rapid development of clean energy, hydro–wind–photovoltaic multi-energy systems require centralized control centers with stronger operational support, coordinated dispatch, and emergency response capabilities. However, safety constraints in real control systems limit their use for operator training, fault handling, and emergency drills. In addition, existing simulation-training systems are still largely oriented toward individual plants or single-energy systems, with limited support for coordinated training in hydro–wind–photovoltaic multi-energy centralized-control scenarios. To address these limitations, this paper reviews the development and research status of hydro–wind–photovoltaic centralized control monitoring systems and simulation training platforms. First, the typical architectures and functions of hydropower, wind power, photovoltaic, and multi-energy centralized control systems are summarized, with emphasis on centralized monitoring, unified management, operational analysis, and coordinated decision support. Second, based on established digital-twin architectures and existing simulation-training technologies, a generalized digital-twin-based simulation training framework for hydro–wind–photovoltaic centralized control is proposed, integrating multi-energy dynamic simulation, centralized-control functions, coordinated dispatch, operator interaction, and training assessment. Finally, the key platform functions are discussed, including high-fidelity virtual environment construction, dynamic signal simulation, coordinated dispatch optimization, operator training and assessment, and emergency drills. This review provides a systematic reference for the development and engineering application of digital-twin-based simulation training platforms for hydro–wind–photovoltaic multi-energy centralized control.

Keywords: hydro–wind–photovoltaic centralized control center; digital twin; simulation training platform architecture; operator simulation training

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1. Introduction

The rapid expansion of renewable energy has accelerated the development of large-scale wind, photovoltaic, and hydropower projects worldwide [1–5]. As shown in Figure 1, renewable electricity generation has increased markedly across major regions, with

China becoming an increasingly important contributor to global renewable power development [6]. However, many renewable energy stations are geographically dispersed and located in remote or mountainous areas, resulting in high operation and maintenance costs, limited information sharing, and difficulties in coordinated management [7,8]. To address these challenges and support unattended or minimally staffed operation [9], clean-energy centralized control centers have increasingly been adopted to realize unified monitoring, management, and coordinated operation of multiple renewable energy stations [10,11].

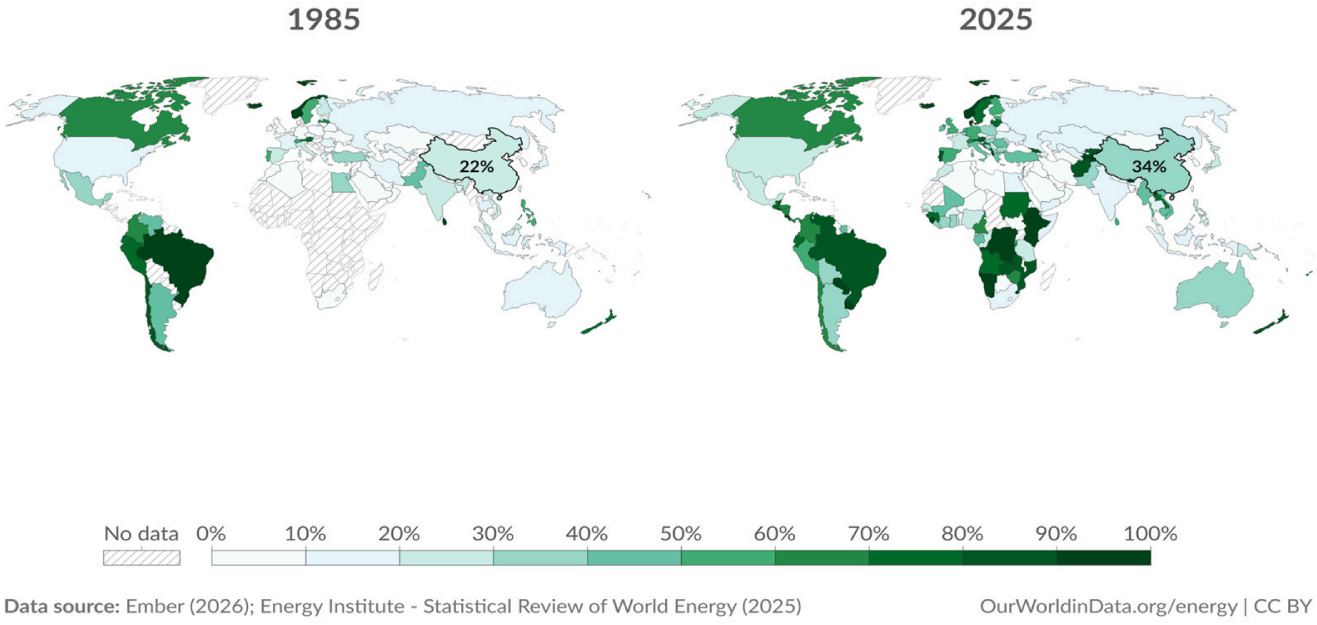


Figure 1. Shares of electricity generation from renewable sources by region, 1985 and 2025. Renewables include photovoltaic, wind, hydropower, bioenergy, geothermal, wave, and tidal sources [6].

Centralized control centers integrate data and operating information from multiple remote stations and provide functions such as real-time monitoring, data analysis, operation management, dispatch support, fault warning, and abnormal-event handling [12–22]. With the increasing number of connected stations and monitoring points, however, operators must process rapidly growing volumes of alarms, event records, and real-time data. Excessive information can obscure critical events and increase the risk of misjudgment, particularly during complex operating conditions and emergencies [23–25]. Operator competence has therefore become an important factor affecting the safe and efficient operation of centralized control centers.

Conventional training methods, including classroom instruction, laboratory exercises, and on-site training, provide limited opportunities to reproduce rare faults and complex emergency scenarios [26]. Although simulation-based training has been applied in power plants [27,28], conventional systems often have limited capability for realistic scenario reconstruction, interactive operation, and coordinated multi-energy simulation. These limitations restrict their applicability to increasingly complex clean-energy centralized control environments.

Recent advances in digital-twin technology [29,30] have created new opportunities for simulation-based training in clean-energy centralized control centers. By constructing virtual environments that reproduce actual operating processes and control logic, digital-twin platforms can support monitoring, operation, fault handling, and emergency training [31]. Combined with three-dimensional visualization or virtual reality technologies, such platforms can further enhance training realism and interaction [32]. Existing studies have demonstrated the effectiveness of virtual simulation in power-system training.

Zhang et al. [33] developed a virtual training platform for hydro-turbine governing systems that supports operation, maintenance, and interactive simulation. Chen et al. [34] proposed a virtual-reality-based training system for hydropower plant operation and maintenance, while Larios et al. [35] developed a renewable-energy training platform integrated with a real SCADA system for wind/photovoltaic/storage applications. However, most existing platforms target individual plants or single-energy systems, with limited support for multi-source data integration, cross-station coordinated monitoring, and comprehensive training in hydro–wind–photovoltaic centralized control scenarios. Therefore, developing a high-fidelity digital-twin-based simulation training platform for multi-energy centralized control centers is important for improving operational safety, emergency response, and coordinated dispatch capabilities.

A structured literature search was conducted to improve the coverage and transparency of this narrative review. The search covered the Web of Science Core Collection, Scopus, IEEE Xplore, ScienceDirect, and the China National Knowledge Infrastructure (CNKI). The primary search included publications from 2000 to April 2026, a period encompassing major developments in centralized-control systems, power-system simulation training, and digital-twin technologies. Earlier representative studies were additionally identified through backward citation tracking when they provided foundational evidence on the early development of hydropower centralized control or power-system simulation. The search terms were organized into three thematic groups: (1) centralized-control-related terms, including centralized control, control center, SCADA, remote monitoring, and multi-station operation, combined with hydropower, wind power, photovoltaic, and hydro–wind–photovoltaic; (2) simulation-training-related terms, including simulation training, operator training, dispatcher training simulator, virtual simulation, and hardware-in-the-loop; and (3) digital-twin-related terms, including digital twin, physical–virtual mapping, and power-system digital twin. Equivalent Chinese terms were used for the CNKI search. Studies were included when they directly addressed centralized-control architectures or functions, multi-energy coordinated operation, power-system simulation training, or digital-twin applications relevant to energy systems. Priority was given to peer-reviewed journal articles and conference papers for identifying general technological trends and supporting cross-study comparisons. Selected standards, technical reports, and engineering publications were also included when they provided implementation details or practical centralized-control architectures that were not sufficiently documented in the academic literature; these sources were used primarily to characterize engineering practice rather than as the sole basis for general conclusions. Duplicate records, studies unrelated to centralized control or operator training, component-level studies lacking system-level relevance, and publications providing insufficient technical information were excluded.

This paper reviews monitoring systems and simulation-based training platforms for hydro–wind–photovoltaic centralized control centers. It first summarizes and compares the development, architectures, and operational functions of hydropower, wind power, photovoltaic power, and multi-energy centralized control systems. On this basis, the requirements of multi-energy centralized-control training are further examined in relation to existing simulation-training and digital-twin technologies. Although current simulation-training platforms have demonstrated effective applications in plant operation, equipment training, and fault handling, most are developed for individual plants or single-energy systems, and their support for multi-station coordination and multi-energy interaction remains limited. Building on established digital-twin architectures, this review therefore synthesizes a generalized training framework that integrates heterogeneous hydro–wind–photovoltaic simulation, multi-station centralized monitoring, coordinated dispatch, abnormal-scenario reproduction, operator interaction, and training assessment within a unified environment.

By extending digital-twin technology to the specific operational and training requirements of hydro–wind–photovoltaic centralized control, the proposed framework connects multi-energy dynamic simulation with operator-oriented training functions while retaining the fundamental physical–virtual, data, service, and communication structure of existing digital-twin architectures. The key functions of the framework, including virtual environment construction, multi-energy signal simulation, coordinated dispatch, operator training and assessment, and emergency drills, are subsequently discussed.

2. Review of Centralized Control Systems for Hydro–Wind–Photovoltaic Multi-Energy Operation

Centralized control centers now support remote operation of wind, photovoltaic, and cascade hydropower stations across large clean-energy bases [36]. This section compares their architectures, core functions, and advanced applications. The comparison clarifies how single-energy monitoring systems are evolving toward multi-energy coordination, intelligent dispatch, and decision support.

2.1. Architecture of Hydro–Wind–Photovoltaic Centralized Control Centers

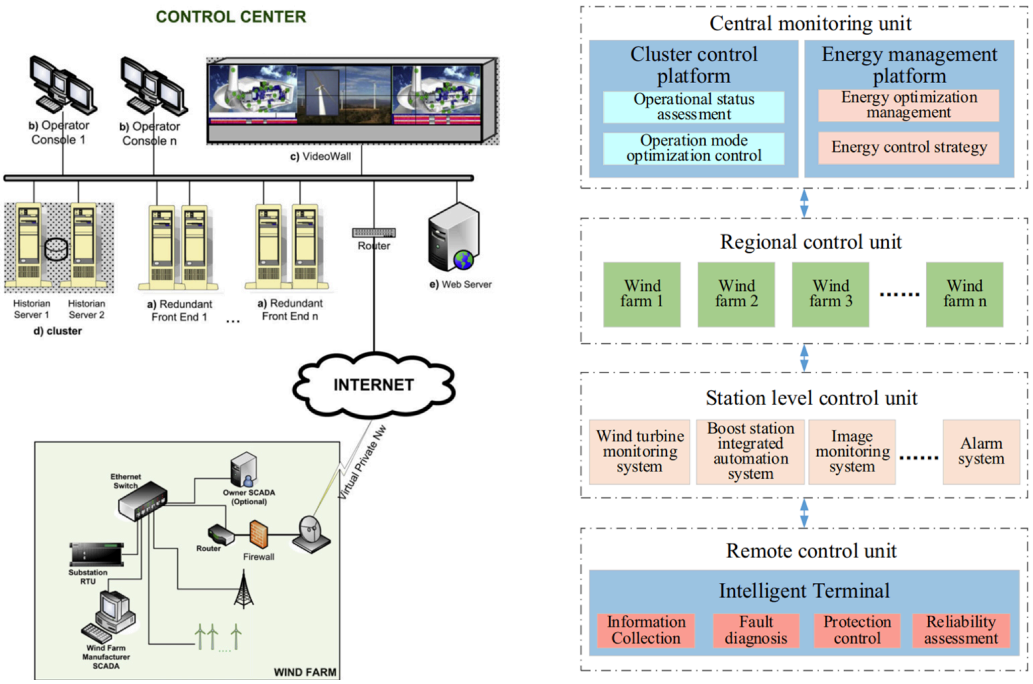
Most centralized control centers adopt hierarchical architectures integrating field sensing, communication networks, data services, and application-level decision-making. Reliable communication infrastructure enables multi-station monitoring, information sharing, and coordinated resource management across geographically distributed renewable energy plants. Compared with decentralized control, centralized control platforms can aggregate operating data from multiple subsystems, provide system-wide situational awareness, and coordinate control or dispatch decisions at the regional level. Such an architecture provides the technical foundation for the unified monitoring, coordinated operation, and optimized management of large-scale renewable energy clusters.

2.1.1. Wind Farm Centralized Control Centers

With the rapid expansion of wind power capacity and the increasing number of geographically distributed wind farms, decentralized operation and management have become increasingly inefficient. Regional centralized control centers have therefore been widely adopted to improve operational efficiency, resource coordination, and economic performance. These systems generally rely on supervisory control and data acquisition (SCADA) technologies [37–40] to integrate operational data from multiple wind farms and support centralized monitoring, dispatch, and management [11]. Due to their long-term application in industrial automation and power-system operation, SCADA-based monitoring and control architectures have become established solutions for practical wind-farm operation. However, their initial functions mainly focus on information acquisition and remote supervision, providing the foundation for further development toward multi-station coordination and intelligent operation.

At the architectural level, wind-farm centralized-control systems typically include hardware infrastructures and hierarchical software structures. Reference [41] presented a representative hardware architecture, shown in Figure 2A, in which multiple wind farms are connected through parallel control and communication subsystems, providing scalable support for centralized data aggregation. Reference [42] further developed a hierarchical remote-control architecture, shown in Figure 2B, which consists of central, regional, station-level, and remote-control units, enabling functions such as monitoring, fault alarming, parameter adjustment, and equipment control. Building on these architectures, Liang et al. [43] proposed a remote centralized-control scheme for regional multi-wind farms by integrating field acquisition, communication transmission, monitoring, forecast-

ing, and dispatch functions, as shown in Figure 3. These developments demonstrate the transition of wind-farm centralized control from basic data acquisition toward regional coordinated operation. Nevertheless, increasing numbers of connected wind farms introduce higher requirements for communication reliability, information consistency, and coordination among heterogeneous subsystems.



(**A**) (**B**)

Figure 2. (**A**) Typical hardware architecture of a wind-farm centralized control center [41]; (**B**) Layered software architecture for remote wind-farm control [42].

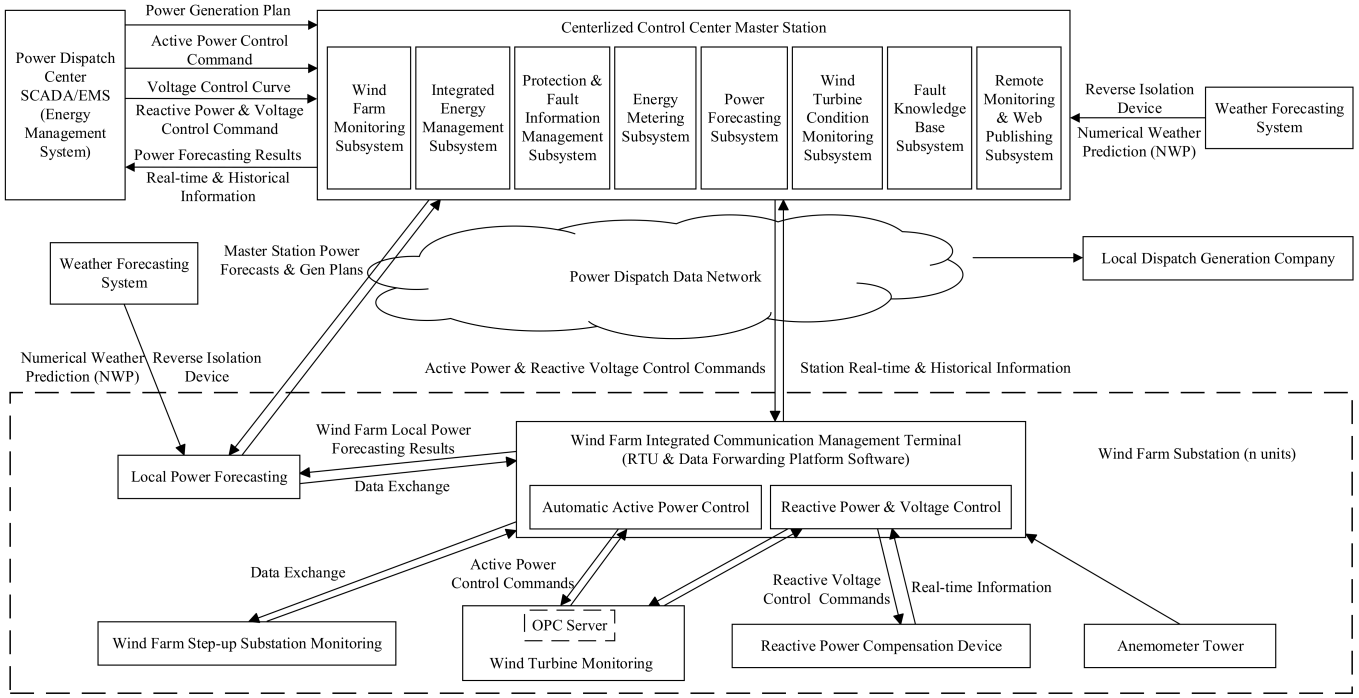
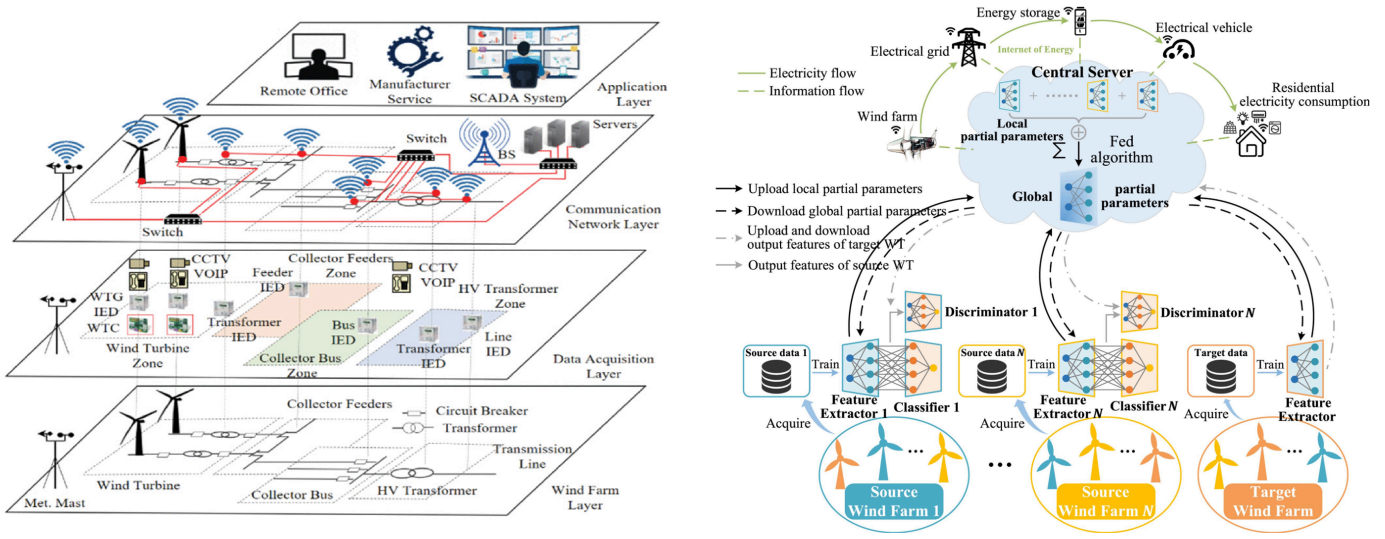


Figure 3. Architecture of the remote centralized control system for wind farms, adapted from Reference [43].

Recent advances in the Internet of Things (IoT), cyber–physical systems (CPSs), and artificial intelligence (AI) have further promoted the evolution of wind-farm centralized control toward intelligent operation [44]. Unlike SCADA-based monitoring and hierarchical control, which have already been widely adopted in practical wind-farm operation, CPS- and AI-enabled approaches are still evolving, with current research focusing mainly on enhancing information interaction, intelligent analysis, and data-driven decision support. Reference [45] proposed a layered CPS architecture that integrates data acquisition, communication, monitoring, and decision support, as shown in Figure 4a. By strengthening the interaction between physical equipment and digital information systems, CPS-based approaches provide improved support for operational analysis and decision-making. However, heterogeneous operating conditions and data characteristics among geographically distributed wind farms remain challenges for information fusion and intelligent model adaptation. To address this issue, Reference [46] introduced a federated transfer learning framework, shown in Figure 4b, for collaborative condition monitoring across heterogeneous wind farms while reducing communication and computational costs. Although this approach provides a promising solution for cross-farm knowledge sharing without centralized raw-data exchange, its practical deployment at large scale requires further validation.



(**a**) (**b**)

Figure 4. (**a**) Architecture of the cyber–physical wind power system [45]; (**b**) An efficient federated transfer learning framework for IoT-based wind farms [46].

International studies have explored wind-farm centralized control from perspectives including SCADA-based condition monitoring [47], predictive maintenance, wind power plant control, and wind control center development. In comparison, Chinese research and engineering applications have been strongly influenced by large-scale onshore wind-power-base development, with greater emphasis on regional centralized monitoring, multi-farm coordination, and integration with power dispatching systems. These differences reflect complementary priorities shaped by deployment scale and operational requirements.

Overall, wind-farm centralized-control systems have evolved from SCADA-based monitoring toward hierarchical management, regional coordination, and intelligent operation. Established technologies, including SCADA monitoring, hierarchical control, and remote centralized operation, have provided solid foundations for large-scale wind-power management, whereas CPS, AI, and federated-learning-based approaches are still developing toward broader engineering applications. However, current systems still face challenges in large-scale heterogeneous operation, particularly in platform interoperability,

cross-station coordination, and the integration of monitoring, forecasting, fault diagnosis, and operational control. Future development should focus on improving heterogeneous data utilization and strengthening the coupling between intelligent analysis and operational control strategies.

2.1.2. Photovoltaic Power Plant Centralized Control Centers

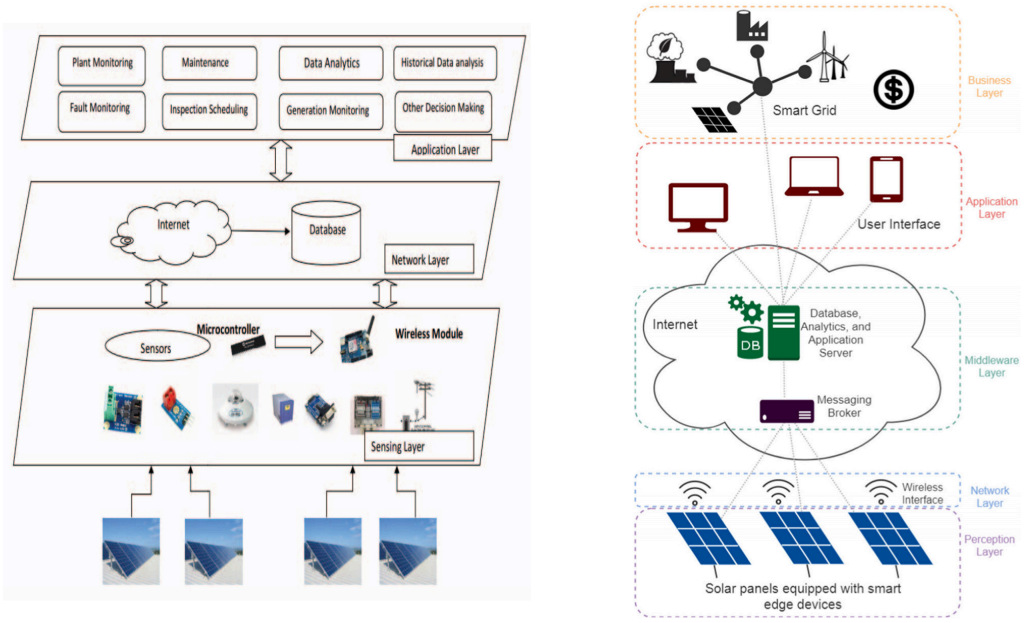
Photovoltaic power plant operation and management have traditionally relied on station-level supervisory control and data acquisition (SCADA) systems for real-time data acquisition, equipment monitoring, performance analysis, and operation and maintenance support [48,49]. Given the large number of distributed components, including photovoltaic modules, inverters, and combiner boxes, SCADA-based systems provide an effective solution for aggregating multi-point operational information and establishing centralized plant-level monitoring. These systems enable operators to evaluate equipment status, generation performance, and operational conditions through integrated data acquisition, visualization, and analysis. However, their functions remain mainly focused on plant-level information collection and equipment supervision, providing limited support for intelligent analysis and coordinated operation among multiple photovoltaic plants.

To address these limitations, photovoltaic monitoring systems have increasingly incorporated the Internet of Things (IoT), wireless sensor networks, and machine-learning technologies [50–53]. Compared with conventional SCADA-based monitoring, these approaches enhance sensing coverage, communication flexibility, and data-driven analysis capability, enabling more accurate condition monitoring and fault diagnosis at equipment and array levels [54]. Beyond equipment- and array-level monitoring, IoT-based architectures at the plant level further integrate data acquisition, communication, fault detection, preventive maintenance, and historical analysis. As shown in Figure 5a, Reference [55] developed an IoT-based remote monitoring system that combines plant operating-condition monitoring, fault detection, preventive maintenance, and historical data analysis, demonstrating the extension of conventional SCADA toward intelligent operation and maintenance. Similarly, Figure 5b shows the IoT architecture proposed in Reference [56] for large-scale photovoltaic power plants, which further integrates sensing, communication, and data-processing functions to improve system scalability and reduce edge-side deployment complexity. These studies indicate that IoT-based photovoltaic monitoring has gradually expanded from basic data acquisition toward integrated plant-level information management, providing important support for intelligent operation and maintenance of large-scale photovoltaic installations.

Beyond plant-level intelligent monitoring, photovoltaic centralized-control systems have gradually developed toward coordinated operation of multiple photovoltaic plants under different deployment contexts. In China, the rapid expansion of utility-scale photovoltaic bases has promoted the development of regional centralized-control centers that integrate centralized data management, energy management, remote operation, and interaction with grid dispatching systems. Meanwhile, international research and engineering practices have focused on both utility-scale photovoltaic control and distributed photovoltaic integration, including smart-grid interaction and distributed energy resource (DER) management, reflecting differences in deployment scales and grid structures. These different development pathways represent complementary approaches: centralized-control architectures emphasize the unified management of clustered photovoltaic resources, whereas DER-oriented approaches focus on improving flexibility and grid interaction capability of distributed photovoltaic resources.

Overall, photovoltaic centralized-control systems have evolved from station-level SCADA monitoring toward intelligent operation and regional multi-plant coordination.

SCADA-based monitoring and plant-level control have become established components of practical photovoltaic operation, whereas IoT, machine-learning, and data-driven approaches remain under continuous development toward broader engineering applications. Existing systems have significantly improved large-scale data acquisition, equipment condition monitoring, fault diagnosis, and operation and maintenance efficiency. However, current photovoltaic centralized-control systems still require further improvement in heterogeneous data integration, interoperability among multiple platforms, and coordinated decision-making that combines monitoring, forecasting, and operational control. Future development should focus on enhancing multi-plant coordination capability and intelligent operational support under increasingly complex grid-integration scenarios.



(**a**) (**b**)

Figure 5. (**a**) IoT-based remote monitoring system for photovoltaic power plants [55]; (**b**) IoT-based architecture for large-scale photovoltaic power plants [56].

2.1.3. Hydropower Station Centralized Control Centers

Compared with wind and photovoltaic power systems, hydropower centralized control has a longer history of engineering application and has developed relatively mature operation and management mechanisms. Early studies on Electricité de France (EDF) documented the large-scale automation and remote operation of hydropower plants, with groups of plants progressively operated or programmed from centralized valley-level control stations [57]. In Korea, Kim et al. [58] further reported a nationwide integrated SCADA architecture designed to shift the operation of multiple hydropower facilities from individual sites to a central operating system.

From the perspective of management functions, existing hydropower centralized-control systems can generally be classified into power dispatching, water dispatching, integrated water–power dispatching, and integrated water–power dispatching, maintenance, and inspection modes [59], as summarized in Figure 6. These modes reflect different levels of automation, dispatch authority, and operation and maintenance integration. In practice, centralized control often evolves from single-function power or water dispatching toward integrated water–power coordination and, ultimately, toward comprehensive dispatching, maintenance, and inspection. These developments are closely associated with the strong coupling between hydropower generation and hydrological processes, which

requires the coordinated management of electrical operation, reservoir conditions, and water resources.

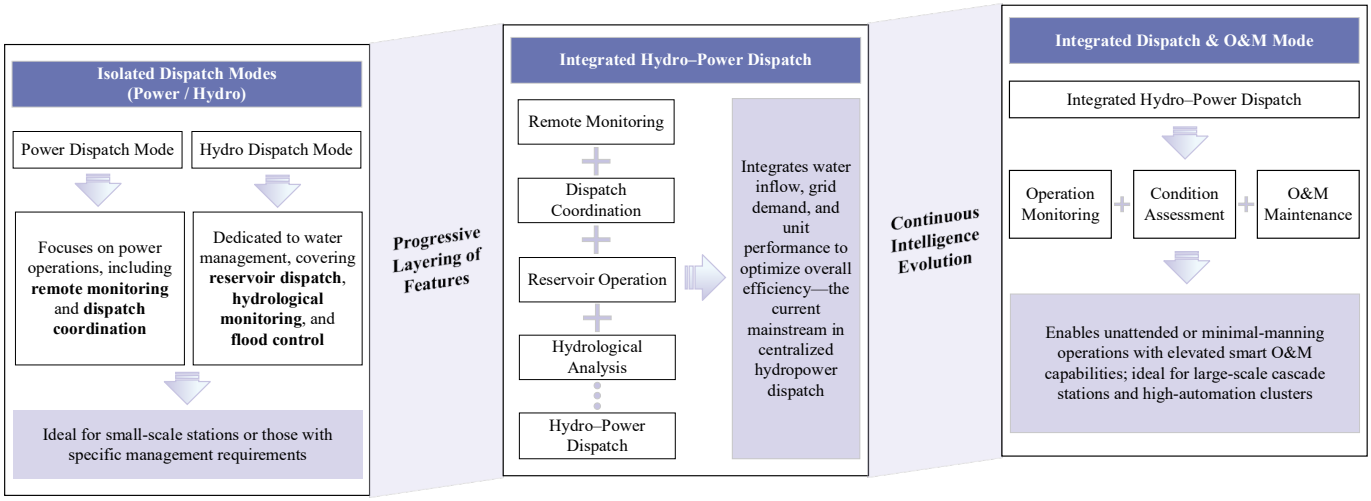


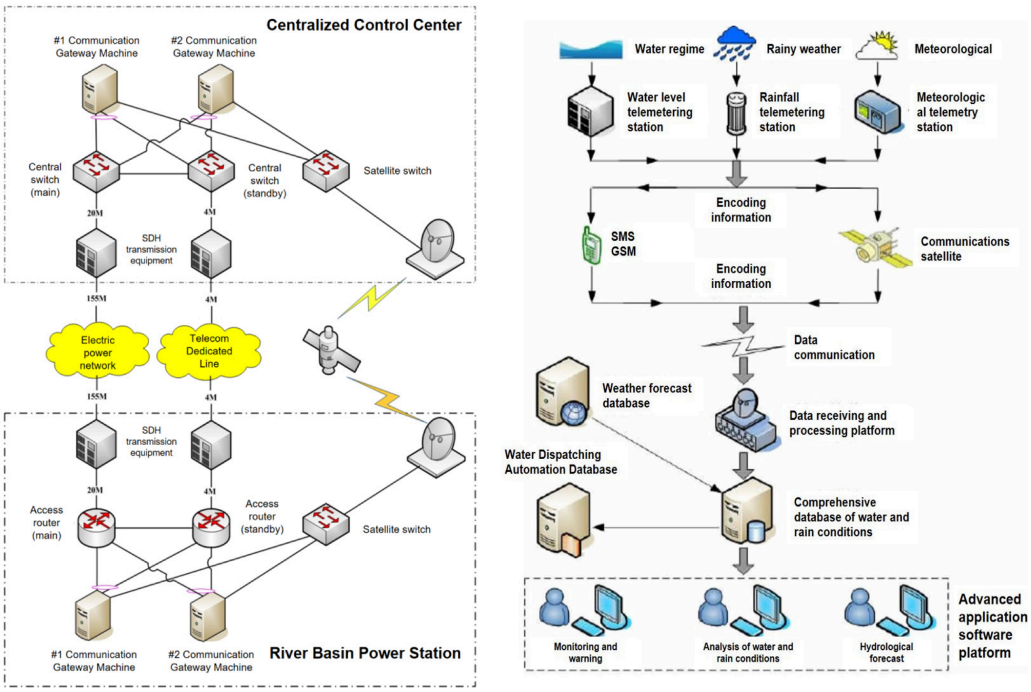
Figure 6. Classification and applicable scenarios of hydropower centralized control operation modes.

Hydropower centralized-control practices across different regions show a common transition from plant-level supervision toward basin- or cascade-level coordination, although their organizational and dispatch structures vary [57–60]. Such systems generally integrate plant operation, hydrological information, reservoir states, forecasting, and dispatch functions to support coordinated management across multiple stations. The Yalong River Centralized Control Center provides a representative basin-level implementation in China [60]. Because this case is documented primarily in an engineering-oriented technical report, it is used here to illustrate a practical implementation rather than as the sole basis for generalizing the characteristics of hydropower centralized-control systems. As shown in Figure 7a, its information-transmission framework supports the centralized acquisition and exchange of operational and hydrological information among cascade stations, while Figure 7b presents the corresponding water-dispatch system integrating monitoring, forecasting, scheduling, and risk analysis. Together, these functions demonstrate how basin-level centralized control can integrate multi-station information and dispatch processes to support coordinated cascade operation.

Recent studies further indicate that hydropower centralized-control systems are evolving toward integrated and service-oriented platforms that combine monitoring, hydrological forecasting, reservoir dispatch, cascade operation, and fault diagnosis within shared data and service environments [61]. Figure 8 presents a representative implementation of this trend, in which computing resources, data management, common services, and application functions are organized within a layered architecture. This layered design demonstrates how previously separate operational functions can be integrated into a unified centralized-control platform, thereby improving information sharing and functional coordination. Despite these advances, such platforms remain under continuous development, particularly in heterogeneous data integration and advanced decision-support capabilities.

Overall, hydropower centralized-control systems have evolved from plant-level monitoring and individual dispatch functions toward integrated water–power coordination, cascade reservoir management, and intelligent centralized platforms. Compared with wind and photovoltaic centralized-control systems, hydropower systems place greater emphasis on the interaction between electrical operation and hydrological processes, requiring coordination among power generation, reservoir regulation, and cascade operation. Existing technologies have established solid foundations for basin-level centralized manage-

ment, while future development will focus on improving intelligent hydropower operation through digital-twin-based system integration, AI-assisted scheduling optimization, and advanced decision-support technologies.



(**a**) (**b**)

Figure 7. (**a**) Information transmission automation framework of the Yalong River Centralized Control Center; (**b**) Water dispatching system of the Yalong River Centralized Control Center [60].

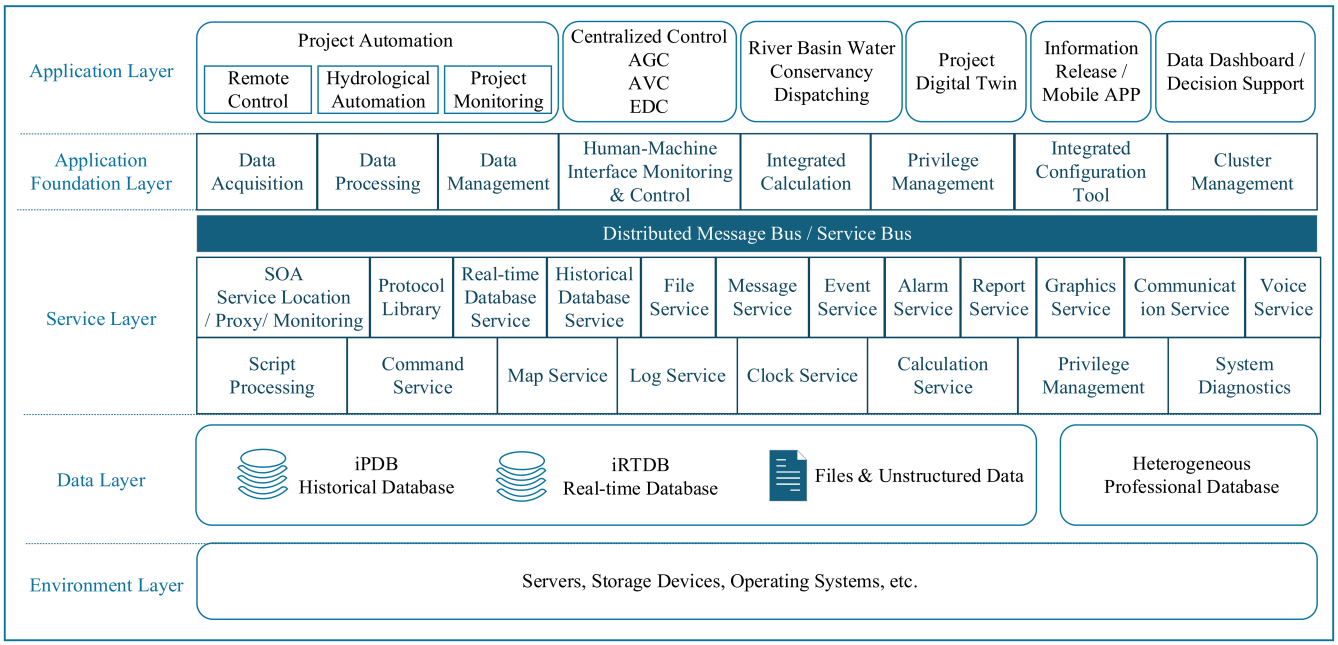


Figure 8. Overall architecture of the intelligent integrated platform for centralized control of cascade hydropower stations, adapted from Reference [61].

2.1.4. Hydro–Wind–Photovoltaic Multi-Energy Centralized Control Centers

With the increasing integration of renewable energy resources, centralized control systems based on individual energy types are becoming insufficient for coordinated operation of heterogeneous power sources. Hydro–wind–photovoltaic multi-energy centralized-

control centers have therefore emerged as an important approach for clean-energy bases [62]. Building on existing hydropower, wind, and photovoltaic monitoring systems, these centers integrate multi-source operational information and control functions to support unified monitoring, coordinated dispatch, and complementary operation among different energy resources.

Existing studies show that multi-energy centralized-control architectures have progressively evolved from functional integration toward platform-based information integration and, more recently, cloud-edge-device collaborative operation [63–65]. The representative architectures shown in Figures 9–11 illustrate different stages of this evolution. Early systems mainly emphasized the unified monitoring and dispatch of hydropower and new-energy stations within a common control environment [63]. Compared with independent energy-specific control systems, these architectures provide a basis for multi-source information sharing and complementary operation among renewable-energy resources, thereby supporting improved resource coordination and renewable-energy utilization. Subsequent integrated platforms further strengthened unified data access, shared services, and the integration of monitoring, analysis, and operational applications [64]. More recent cloud-control approaches have extended these capabilities through cloud-based optimization, edge-side coordination, and field-level sensing and control [65]. Overall, these studies reveal a common transition from the simple aggregation of heterogeneous energy stations toward deeper integration of data, operational functions, and decision-support capabilities.

Overall, hydro–wind–photovoltaic centralized-control systems have evolved from independent energy monitoring toward multi-source information integration, platform-based management, and intelligent coordination. Existing multi-energy platforms have provided foundations for unified monitoring and coordinated operation across heterogeneous energy resources, while advanced functions such as intelligent optimization and cross-system decision support are still under continuous development.

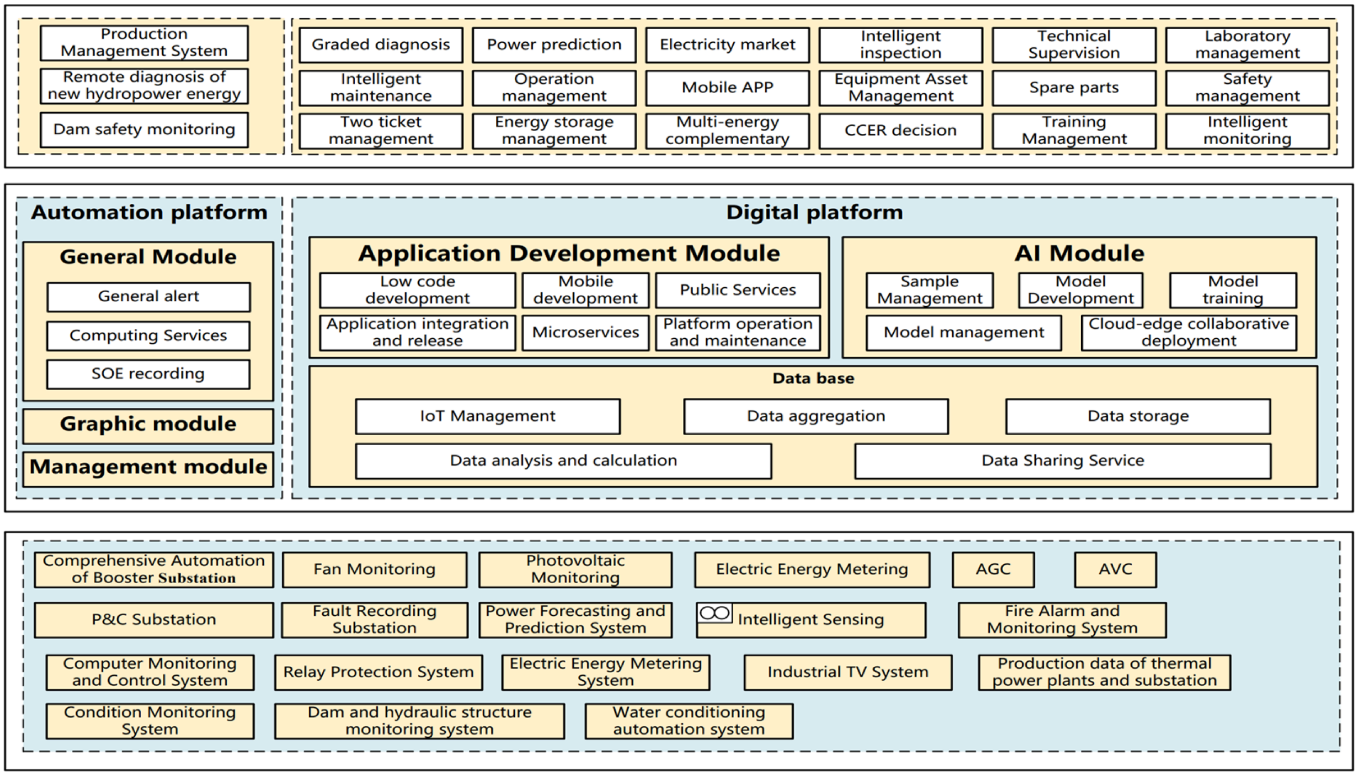


Figure 9. Centralized control center architecture for hydropower and new-energy systems [63].

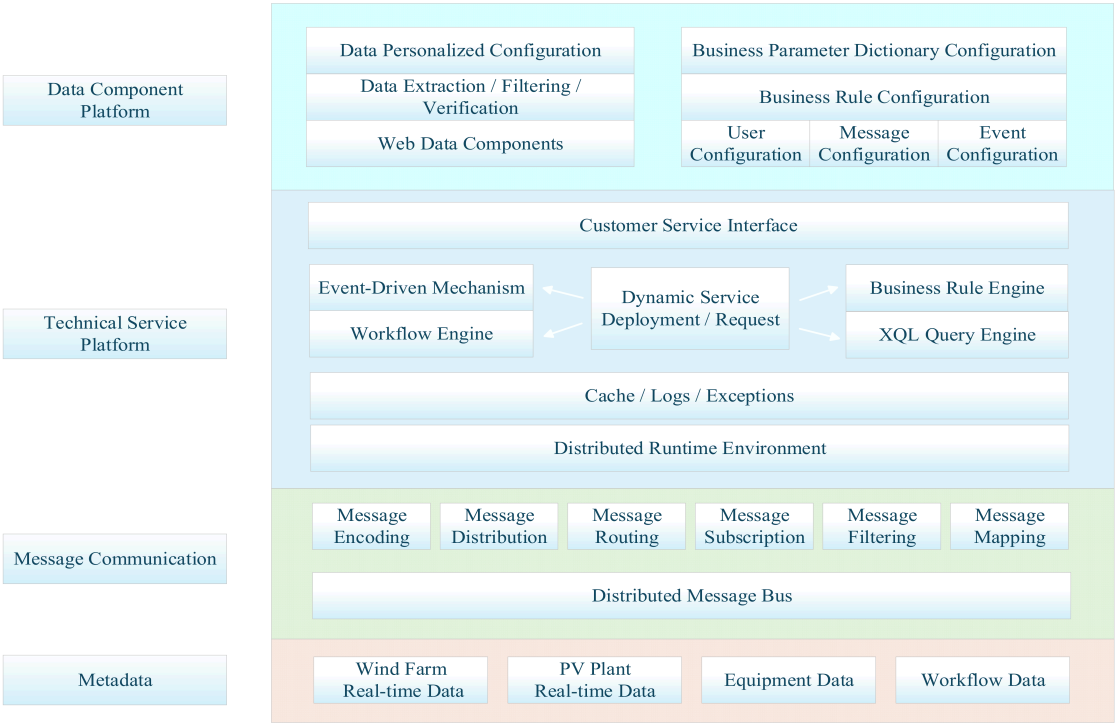


Figure 10. Overall architecture of the integrated platform for new-energy centralized control centers, adapted from Reference [64].

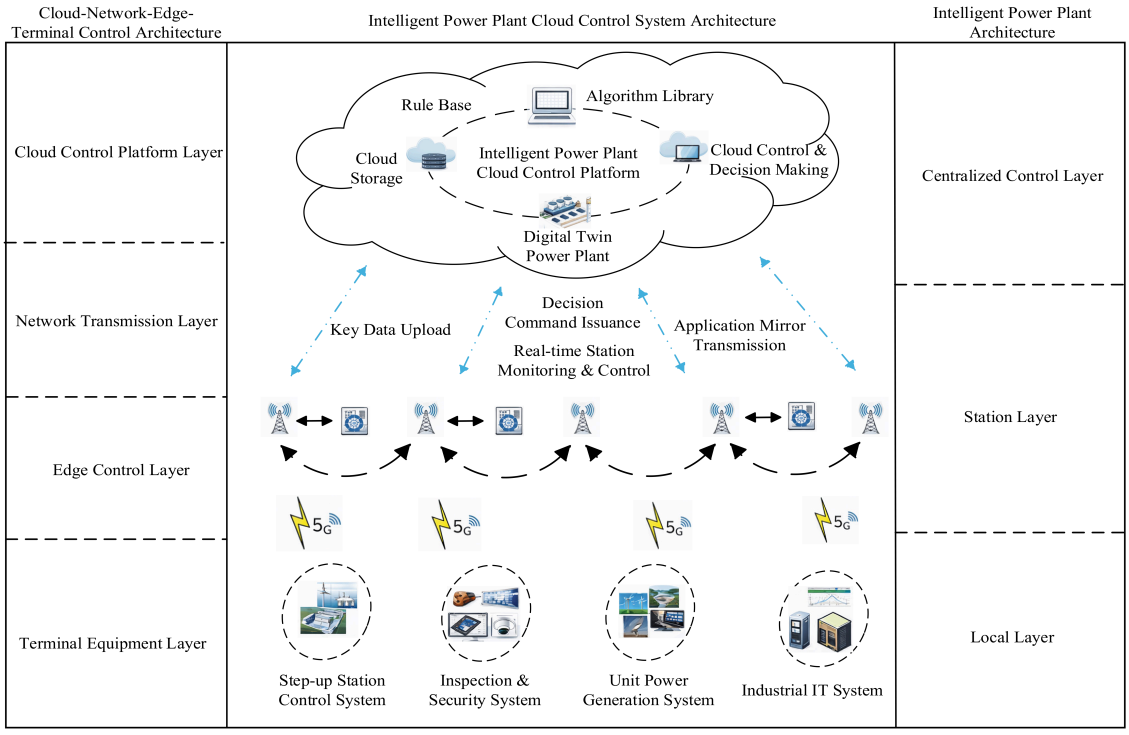


Figure 11. Cloud–network–edge–device architecture of the cloud control system for intelligent power plants, adapted from Reference [65].

2.1.5. Comparative Characteristics and Technology Evolution of Centralized Control Systems

Although wind, photovoltaic, and hydropower centralized-control systems share common functions such as data acquisition, communication, monitoring, and remote operation, their operational characteristics and functional priorities differ significantly. Wind and photovoltaic systems are characterized by geographically distributed equipment and

variable renewable generation, requiring stronger capabilities in data-driven monitoring, generation forecasting, and coordinated operation. In contrast, hydropower systems involve additional hydrological processes, reservoir states, and cascade coupling, resulting in greater emphasis on water–power coordination, reservoir regulation, and long-term dispatch. These differences have shaped distinct centralized-control architectures and development pathways for different energy sources.

Despite these differences, the three types of centralized-control systems show a broadly similar technological evolution from basic monitoring and remote operation toward integrated analysis and intelligent decision support. From the perspective of technology maturity, SCADA-based monitoring, remote operation, and hierarchical control have reached relatively mature levels of engineering application, while cross-energy coordination, heterogeneous data fusion, AI-assisted decision support, and digital-twin-enabled intelligent operation are still under continuous development and require further large-scale practical validation. This difference in technological maturity also indicates that the transition from single-energy centralized control to multi-energy coordination is not simply an extension of existing functions, but requires deeper integration of heterogeneous data, operational models, and decision-making mechanisms.

Accordingly, the evolution toward hydro–wind–photovoltaic centralized control represents a transition from independent energy management toward integrated multi-energy coordination. By combining hydropower regulation capability with the complementary characteristics of wind and photovoltaic generation, multi-energy centralized-control systems provide a technical foundation for the coordinated operation of large-scale clean-energy bases. Compared with single-energy centralized control, these systems require not only unified information platforms but also cross-energy coordination mechanisms and advanced decision-support capabilities. Centralized-control architectures are therefore gradually shifting from single-energy supervision toward multi-energy integration, coordinated operation, and intelligent decision support. The corresponding operational functions and advanced applications are discussed in Section 2.2.

2.2. Operational Functions of Hydro–Wind–Photovoltaic Centralized Control Centers

2.2.1. Fundamental Operational Functions

Hydro–wind–photovoltaic centralized control centers generally provide four fundamental operational functions: data acquisition and processing, operational monitoring and remote control, fault alarming and handling, and operation management, as summarized in Figure 12. These functions form the basic operational framework for centralized management of geographically distributed hydropower, wind, and photovoltaic stations.

Data acquisition and processing provide the information foundation of centralized control by integrating real-time operating data from multiple stations and performing validation, preprocessing, storage, and sharing. Operational monitoring and remote control enable operators to supervise station and equipment status and execute authorized remote operations. Fault alarming and handling identify abnormal conditions, classify and record alarms, and support timely operator response. Operation management further integrates dispatch instructions, operation plans, multi-station coordination, and operational records to support standardized and unified management across distributed stations. These basic functions are common to most centralized control systems and provide the data, control, and management foundation for higher-level intelligent applications. As the number of connected stations increases and multi-energy operation becomes more complex; however, these fundamental functions alone are no longer sufficient to support coordinated operation and advanced decision-making, creating a growing demand for higher-level functional applications.

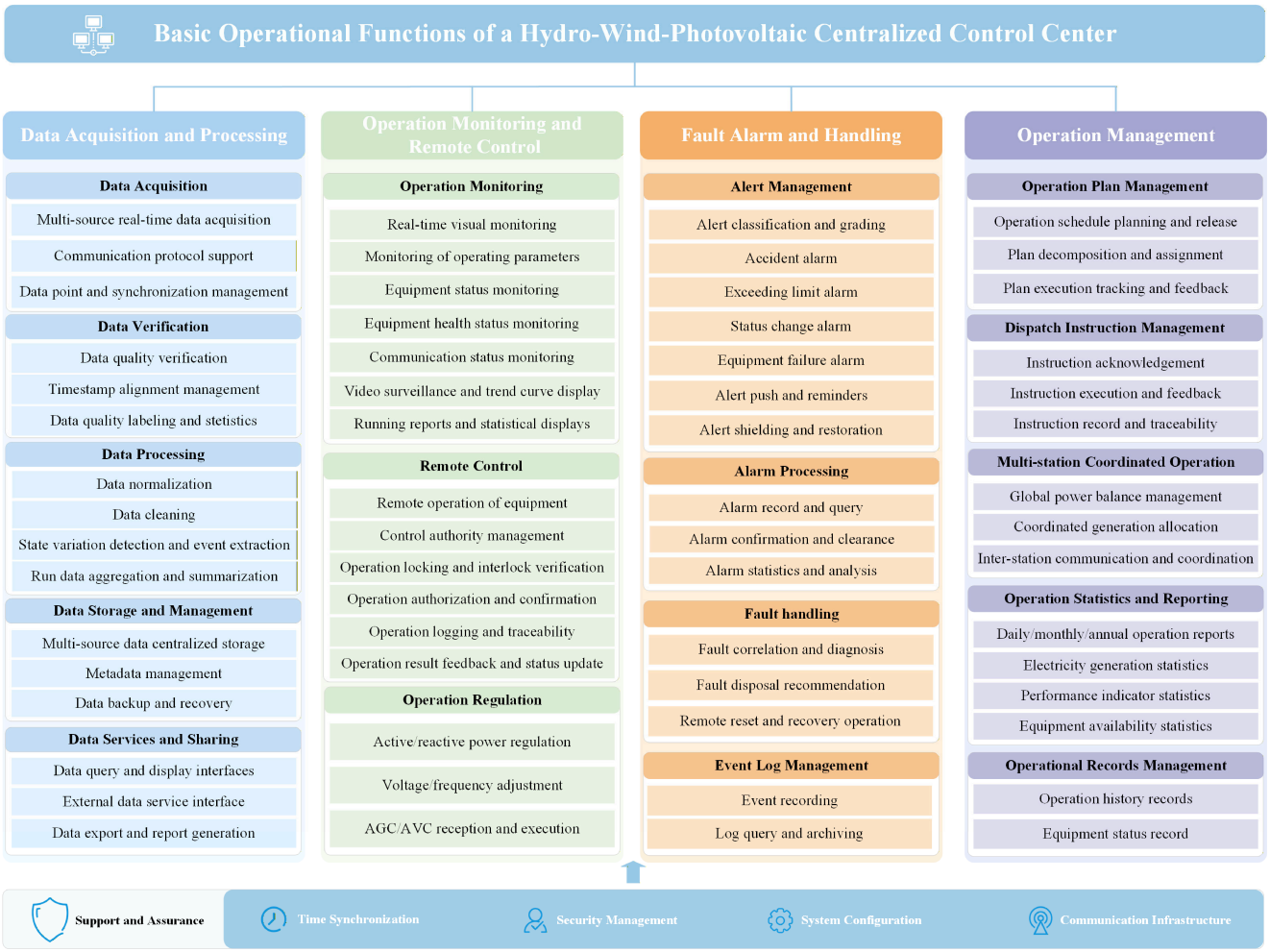


Figure 12. Fundamental functions of the Hydro-Wind-Photovoltaic centralized control center.

2.2.2. Advanced Functional Applications

The focus of these advanced applications varies with the operational characteristics of different energy sources. As summarized in Table 1, hydropower centralized control emphasizes hydrological forecasting, reservoir and cascade dispatch [66], and intelligent alarm management; wind power systems focus more on power forecasting, generation dispatch [67], condition monitoring, and fault early warning [47]; photovoltaic systems place greater emphasis on condition assessment, intelligent inspection, and operation and maintenance. Hydro–wind–photovoltaic centralized control further integrates these functions to support complementary coordination and multi-energy optimal dispatch [68–70].

With the increasing integration of multiple energy sources, advanced applications are shifting from single-energy optimization toward cross-station and multi-energy coordination. Wind and photovoltaic systems have developed relatively strong capabilities in forecasting, condition monitoring, and data-driven operation, whereas hydropower centralized control provides more mature functions for reservoir regulation, cascade coordination, and multi-timescale dispatch. These capabilities are complementary rather than directly interchangeable. Their integration in hydro–wind–photovoltaic centralized control requires consistent data interfaces, coordination among heterogeneous operational models, and decision mechanisms that account simultaneously for renewable-generation variability and hydropower regulation constraints. Consequently, the main challenge is no longer the availability of individual monitoring or optimization functions, but their effective integration into a unified operational and decision-support environment.

Table 1. Comparative summary of advanced applications in centralized control systems.

Centralized Control Object	Representative References	Advanced Functions	Main Characteristics
Wind farms	[42,67]	Power forecasting, generation dispatch, condition monitoring, fault early warning	Focuses on uncertainty of wind generation, multi-farm power allocation, and equipment-condition awareness
Photovoltaic plants	[71,72]	Intelligent inspection, condition assessment, 3D-assisted O&M	Characterized by large numbers of distributed devices and fine-grained monitoring points; emphasizes anomaly identification and O&M efficiency
Hydropower/cascade hydropower	[22,73–76]	Hydrological forecasting, intelligent alarm, reservoir and cascade dispatch	Strong coupling with hydrological processes and reservoir constraints; emphasizes multi-timescale regulation and cascade coordination
Hydro–wind–photovoltaic systems	[8,68–70]	Multi-energy coordinated control, complementary dispatch, optimal power allocation	Integrates heterogeneous energy sources and exploits hydropower flexibility to coordinate variable wind and photovoltaic generation

Overall, existing centralized control systems have developed relatively mature operational and intelligent application functions. However, these systems are designed primarily for real-time production operation rather than operator training. For safety and reliability reasons, real centralized-control systems cannot be freely used for fault injection, incorrect-operation testing, repeated emergency drills, or deliberate modification of operating conditions, because such actions may interfere with normal power production and grid operation. Although these systems can support monitoring, forecasting, dispatch, and fault diagnosis during actual operation, they generally lack mechanisms for controllable fault injection, repeated scenario reconstruction, operator-behavior recording, and quantitative training assessment. Therefore, a separate simulation-based training environment is required to reproduce the operational logic and multi-energy interactions of the real centralized-control system without affecting actual production. Such a platform should extend beyond interface replication to reproduce coordinated control processes, abnormal-event evolution, operator actions, and system responses under different training scenarios [77–80]. This provides the functional basis for the digital-twin-based simulation training framework discussed in the following sections.

3. Digital Twin-Driven Simulation Training Platform for Hydro–Wind–Photovoltaic Centralized Control: Architecture and Technical Framework

3.1. Status and Requirements of Power Simulation Training Platforms

To meet the demand for safe and repeatable operator training, power simulation systems have been progressively developed for thermal power plants, nuclear power plants, substations, and power grids, initially focusing on equipment operation, start-up and shutdown, protection actions, and fault-handling exercises [81–83]. With advances in numerical simulation and computing technology, real-time digital simulation platforms, including RTDS [84,85], RT-LAB [86], Typhoon [87], ePHASORSIM [88], CloudPSS [89,90], and ADPSS [91], have further improved the real-time performance, model fidelity, and scale of power-system simulation. These platforms provide important technical support for control and protection validation, hardware-in-the-loop testing, and complex system analysis; however, their primary purpose remains engineering simulation and equipment or control-system testing rather than operator-centered training and competency assessment.

Operator-oriented simulation platforms have therefore developed along a complementary pathway, with increasing emphasis on operational process reproduction, human–machine interaction, fault-handling exercises, and training scenarios. Table 2 compares representative simulation and training approaches in terms of real-time modeling, scenario

reproduction, training capability, and major implementation limitations. Rather than representing a simple progression in which one platform type completely replaces another, these approaches exhibit different technical strengths and application priorities.

Table 2. Comparison of representative power-system simulation and training approaches.

Platform Type	Real-Time/Modeling	Scenario Capability	Training Capability	Main Limitation
Real-time digital simulation and HIL platforms [84–91]	Strong real-time and dynamic simulation capability	Electrical faults, control and protection testing	Limited operator-oriented interaction; mainly for engineering testing	Requires detailed models and additional training interfaces
Dispatcher/integrated-control simulator [92]	Reproduces dispatch and control processes	Typical operating and dispatch scenarios	Strong procedural-operation training	Limited support for multi-energy coordination and quantitative assessment
Real-time electromagnetic-transient training [93]	High-fidelity real-time simulation	Routine operation, faults, and control-strategy testing	Supports interactive operation and event recording	Application-specific and dependent on dedicated simulation hardware
3D/virtual simulation training [94,95]	Strong visualization; model fidelity depends on underlying simulation	Equipment operation, inspection, and fault scenarios	Strong interaction and spatial cognition	Limited multi-energy dynamic coupling
Digital-twin-based systems [96–98]	Physical–virtual mapping and dynamic data synchronization	State reproduction, prediction, and scenario analysis	Potential for integrated interaction and assessment	Training applications remain limited; validation, interoperability, and scalability require further study

The comparison shows that different simulation approaches address different dimensions of training requirements. Real-time digital simulation platforms provide strong dynamic-modeling and testing capabilities, but operator interaction and training assessment are usually not their primary objectives. Dispatcher-oriented simulators reproduce operational procedures and control processes more directly, whereas three-dimensional platforms improve interaction and spatial cognition but do not inherently guarantee high-fidelity multi-energy dynamic simulation. Digital-twin technology further introduces physical–virtual synchronization and continuous data-model interaction, but existing energy digital-twin studies remain predominantly focused on monitoring, analysis, prediction, and supervisory applications rather than complete operator-training systems [92–98].

For hydro–wind–photovoltaic centralized-control training, these capabilities therefore need to be combined rather than adopted independently. The required platform should simultaneously support heterogeneous multi-energy dynamic models, coordinated-control processes, controllable abnormal and fault scenarios, operator interaction, training-process recording and assessment, and scalable integration of multiple geographically distributed stations. From this perspective, digital-twin technology provides a promising integration mechanism, but its application to comprehensive hydro–wind–photovoltaic centralized-control training remains at an emerging stage and requires further integrated implementation and practical validation.

3.2. Technical Support of Digital Twin Technology

Digital twin technology establishes a dynamic connection between physical systems and their virtual representations through data and models, enabling state representation, analysis, prediction, and optimization. Its development has evolved from early physical–virtual representations toward dynamically updated, data-connected, and increasingly standardized models [99–116], with representative milestones summarized in Figure 13. In power systems, digital twins extend conventional offline simulation by emphasizing physical–virtual mapping, continuous state synchronization, and dynamic model updating. By integrating mechanism-based models with historical and real-time

operating data, digital twins can support condition monitoring, predictive maintenance, dispatch optimization [117], fault tracing [118], multi-energy simulation, and intelligent decision support [119]. A representative five-dimensional digital-twin architecture consists of the physical entity, virtual entity, connection, data, and service components, as shown in Figure 14 [98]. These components provide the basic technical structure for linking physical power systems with virtual models and application services.

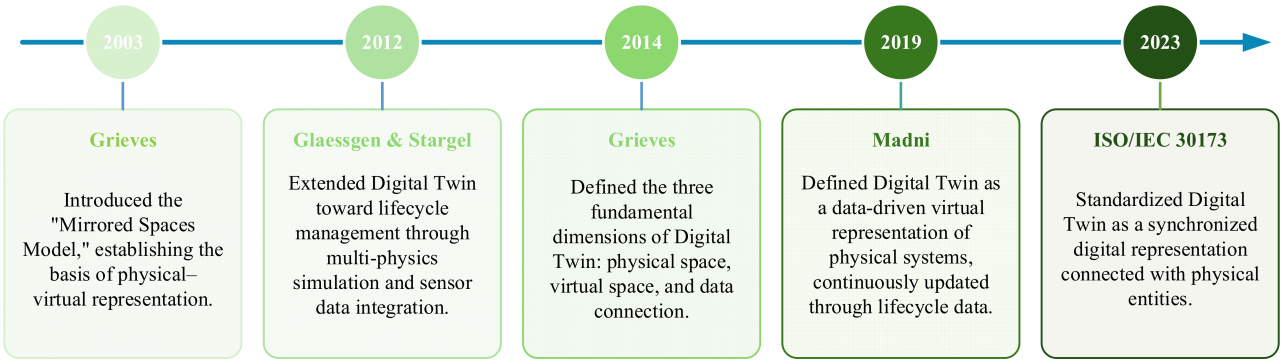


Figure 13. Evolution of the digital-twin concept [112–116].

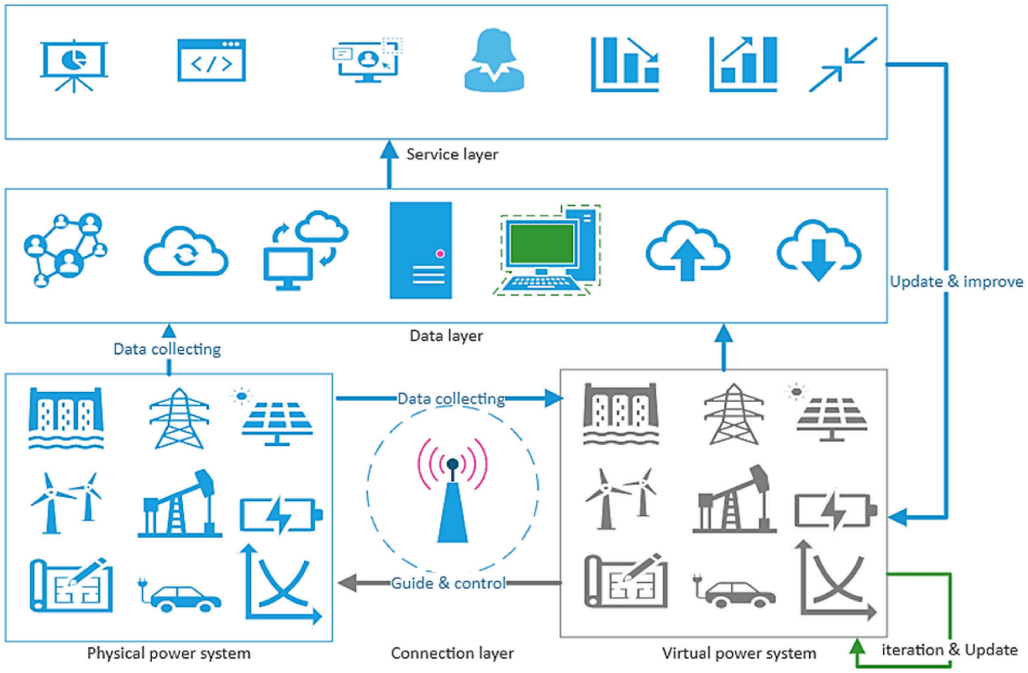


Figure 14. Digital twin architecture for power systems [98].

For hydro–wind–photovoltaic centralized-control training, these digital-twin capabilities provide three main forms of technical support. First, physical–virtual mapping enables the operating states of geographically distributed hydropower, wind, and photovoltaic stations to be represented within a unified virtual environment. Second, the integration of physical models and operational data supports multi-energy dynamic simulation, abnormal-condition reproduction, and coordinated-dispatch analysis. Third, the combination of fault rules, operating procedures, and assessment mechanisms provides a basis for interactive drills, process replay, and quantitative training evaluation. Therefore, digital-twin technology provides an appropriate technical foundation for integrating multi-energy simulation, centralized-control functions, operator interaction, and training assessment within a unified simulation-training environment.

3.3. Architecture of a Digital Twin-Based Simulation Training Platform

Building on the centralized-control architectures and operational functions reviewed above, this study further considers the architecture of an actual hydro–wind–photovoltaic centralized-control system in a river basin. On this basis, established digital-twin architectures and existing simulation-training technologies are incorporated to develop a generalized framework for hydro–wind–photovoltaic centralized-control training, as shown in Figure 15. The framework retains the fundamental digital-twin structure for linking physical systems, virtual models, data, services, and communication, and further extends it according to the requirements of multi-energy centralized-control training. Specifically, hydropower, wind, and photovoltaic operating information and models are integrated within a common virtual environment; centralized monitoring, coordinated dispatch, fault handling, and emergency-response functions are mapped into training applications; and operator interaction and training assessment are incorporated to support interactive and repeatable training. Accordingly, the framework is organized into a physical perception layer, data layer, digital-twin layer, functional application layer, human–machine interaction layer, and communication network.

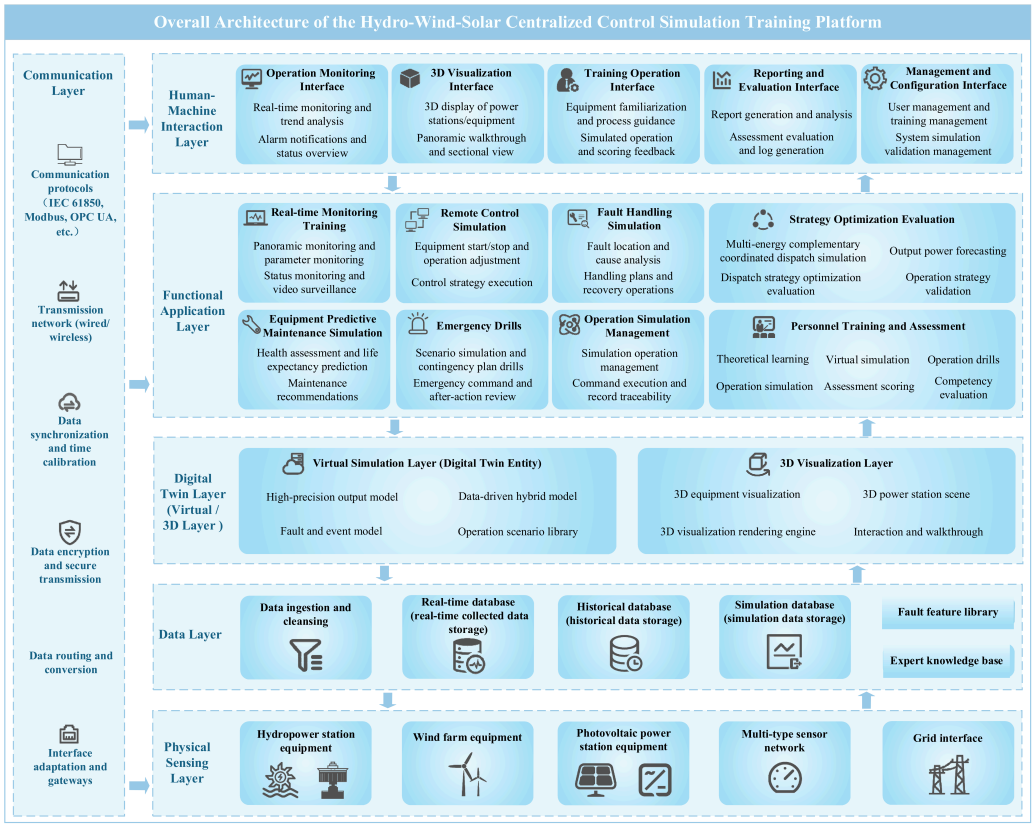


Figure 15. Overall architecture of the digital-twin-based simulation training platform for hydro–wind–photovoltaic centralized control.

The physical perception and data layers provide the information basis for virtual-system construction and training-scenario generation. Real-time and historical operating data from hydropower, wind, and photovoltaic stations can be acquired through standardized data interfaces and integrated with simulation data, fault records, and operational knowledge. Real operating data can support model calibration and validation, state synchronization, scenario initialization, and the reconstruction of representative operating conditions, whereas simulated data provide controllable inputs for training scenarios, fault injection, and operator-response simulation. This combination enables the platform

to reproduce realistic operating conditions while maintaining the flexibility required for repeatable and configurable training. In practical applications, however, communication delays, missing measurements, inconsistent sampling intervals, and variations in field-data quality may affect the timeliness and accuracy of physical–virtual synchronization.

The digital-twin layer provides the main simulation capability by combining mechanism-based and data-driven models with virtual visualization. It reproduces equipment states, multi-energy operating processes, control logic, and abnormal-event evolution, while three-dimensional visualization can be introduced when spatial interaction or equipment cognition is required. The objective of this layer is therefore not merely visual reproduction, but dynamic representation of the operating behavior of the centralized-control system.

The functional application layer maps the operational functions of real centralized control centers into training-oriented scenarios, including monitoring and remote-control exercises, fault handling, emergency drills, hydro–wind–photovoltaic coordinated dispatch, and operator assessment. The human–machine interaction layer provides interfaces for operation, scenario selection, command input, feedback, and training review. Together, these layers enable operators to interact with simulated centralized-control processes rather than passively observe predefined scenarios.

The communication network connects the physical, virtual, and application environments and supports the exchange of data and control information. Standard industrial communication protocols, including IEC 61850 [120], Modbus, and OPC UA, can be adopted according to the connected systems, together with synchronization and cybersecurity mechanisms to maintain data consistency and communication reliability. Because this layer carries operational data and control information across multiple system components, adequate cybersecurity protection is also essential. Unauthorized access, malicious data manipulation, and communication attacks may otherwise compromise data integrity, communication reliability, and the trustworthiness of the virtual training environment.

Overall, the framework extends the architecture of an actual hydro–wind–photovoltaic centralized-control system in a river basin by incorporating established digital-twin and simulation-training technologies. Its main contribution lies in integrating multi-energy dynamic simulation, centralized-control and coordinated-dispatch functions, abnormal-scenario reproduction, operator interaction, and training assessment within the same digital-twin-based framework. Thus, the proposed framework has a practical centralized-control architecture as its engineering basis while extending it toward simulation-training applications. However, the fully integrated framework has not yet undergone comprehensive system-level validation, and its real-time performance and engineering applicability require further verification.

4. Key Functions of the Simulation Training Platform for Hydro–Wind–Photovoltaic Centralized Control

4.1. High-Fidelity Virtual Environment

A high-fidelity virtual environment provides the basic carrier for reproducing centralized-control scenarios. Existing power training systems increasingly combine three-dimensional visualization with dynamic simulation models to represent equipment structures, spatial relationships, operating states, and control processes [121–125]. Compared with conventional static interfaces, this approach improves equipment cognition and allows operating-state changes, alarms, switching actions, and fault locations to be presented more intuitively.

For hydro–wind–photovoltaic centralized control, visual fidelity alone is insufficient. The virtual environment must also reflect the operating logic and dynamic behavior of hydropower units, wind turbines, photovoltaic systems, substations, and associated control

systems. Therefore, high-fidelity training environments are increasingly characterized by the integration of 3D visualization, dynamic operational models, and real-time or historical data. Such integration enables the virtual environment to reproduce not only equipment appearance but also state transitions and fault evolution, providing a more realistic basis for operational training and scenario analysis. However, constructing and continuously maintaining detailed 3D or VR assets for large numbers of geographically distributed stations can require substantial development effort and resources. Therefore, the required level of visual fidelity should be determined by specific training objectives rather than maximized indiscriminately.

4.2. Dynamic Signal Simulation of Multiple Energy Sources

Dynamic signal simulation provides the time-varying virtual operating signals required to drive the simulation-training process. While real-time and historical operating data can support model calibration, state initialization, synchronization, and the construction of representative scenarios, controllable simulated signals are required to reproduce operating conditions that cannot be freely created in real systems. Once a training scenario is initiated, multi-energy simulation models continuously generate signals such as power output, voltage, current, equipment status, alarms, and control responses according to predefined operating conditions, renewable-resource variations, fault settings, control logic, and operator actions. These signals are then supplied to the simulated monitoring, coordinated-dispatch, fault-handling, and human–machine interaction functions, allowing the virtual centralized-control system to evolve dynamically throughout the training process.

The main challenge arises from the heterogeneous dynamic characteristics of different energy sources. Hydropower output is closely coupled with water head, flow, reservoir operation, unit regulation, and cascade interactions [126,127], whereas wind and photovoltaic generation are strongly affected by meteorological variability and forecasting uncertainty. Multi-energy signal simulation therefore requires the coordinated use of mechanism-based models, data-driven methods, historical operating data, and forecasting models [126]. Such a hybrid modeling approach can reproduce both deterministic control responses and the stochastic variations associated with renewable-energy generation.

Data-driven forecasting methods, including deep learning, transfer learning, and temporal feature extraction, can complement mechanism-based models by improving the representation of renewable-energy variability in training scenarios. Figure 16 illustrates one representative multi-site wind-speed prediction approach based on cross-site data learning [7]. Such methods can support the generation of realistic renewable-energy trajectories, although the choice of forecasting model should depend on data availability, the required temporal resolution, and the specific objectives of the training scenario.

For simulation training, however, higher model fidelity does not necessarily imply better practical performance. Because operators need to interact with the simulated system in real time, the level of model detail must also be compatible with the computational capability of the platform. As the number of simulated stations, dynamic components, and coupled processes increases, the computational cost of high-fidelity multi-energy simulation can rise substantially, potentially affecting real-time performance. The practical objective is therefore to achieve sufficient dynamic fidelity for centralized monitoring, coordinated dispatch, fault drills, and operator decision-making while maintaining acceptable computational efficiency and real-time responsiveness.

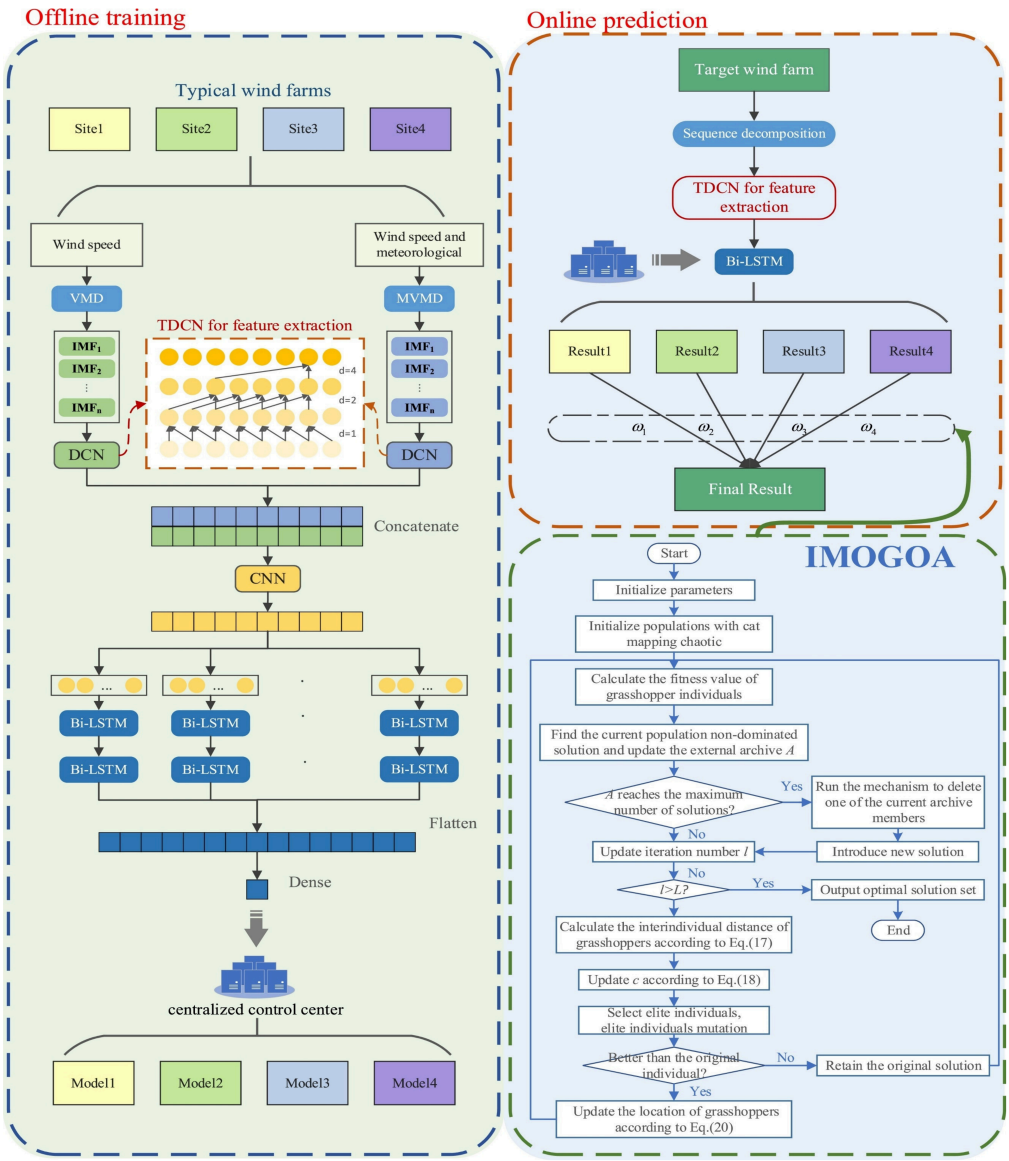


Figure 16. Framework of the multi-site wind speed prediction model based on multi-layer feature fusion and transfer learning [7].

4.3. Coordinated Dispatch Optimization for Multi-Energy Complementarity

Coordinated dispatch is a distinctive function of hydro–wind–photovoltaic centralized control. The variability of wind and photovoltaic generation increases power-balance and dispatch uncertainty, whereas hydropower can provide flexible regulation across different time scales [128–131]. Accordingly, existing studies have gradually expanded from short-term power balancing toward coordinated optimization, dispatch-performance evaluation, and multi-scenario assessment [132–135].

At the operational level, coordinated dispatch primarily exploits the flexible regulation capability of hydropower to compensate for fluctuations in wind and photovoltaic generation. Short- and ultra-short-term optimization models have therefore been developed to coordinate generation adjustments among cascade hydropower stations and variable renewable-energy sources. For example, Ref. [136] investigated ultra-short-term cascade dispatch for suppressing wind and photovoltaic fluctuations. For centralized-control training, however, obtaining an optimal dispatch solution is only part of the requirement. Operators also need to understand how alternative strategies affect system reliability, renewable-energy accommodation, operating economy, and regulation requirements, par-

ticularly under varying resource and operating conditions. Existing studies have therefore extended coordinated dispatch from short-term optimization toward multi-scenario and longer-term performance assessment, considering variations in hydrological conditions, renewable-energy availability, and system operating states [137]. Figure 17 presents an evaluation framework for wind-photovoltaic-hydro complementarity [70], illustrating how multiple performance dimensions can be incorporated into the comparison of coordinated-operation strategies. Within a simulation-training environment, such approaches can be used to construct contrasting operating scenarios, reproduce the consequences of different dispatch decisions, and help operators understand the trade-offs among alternative strategies under changing system conditions.

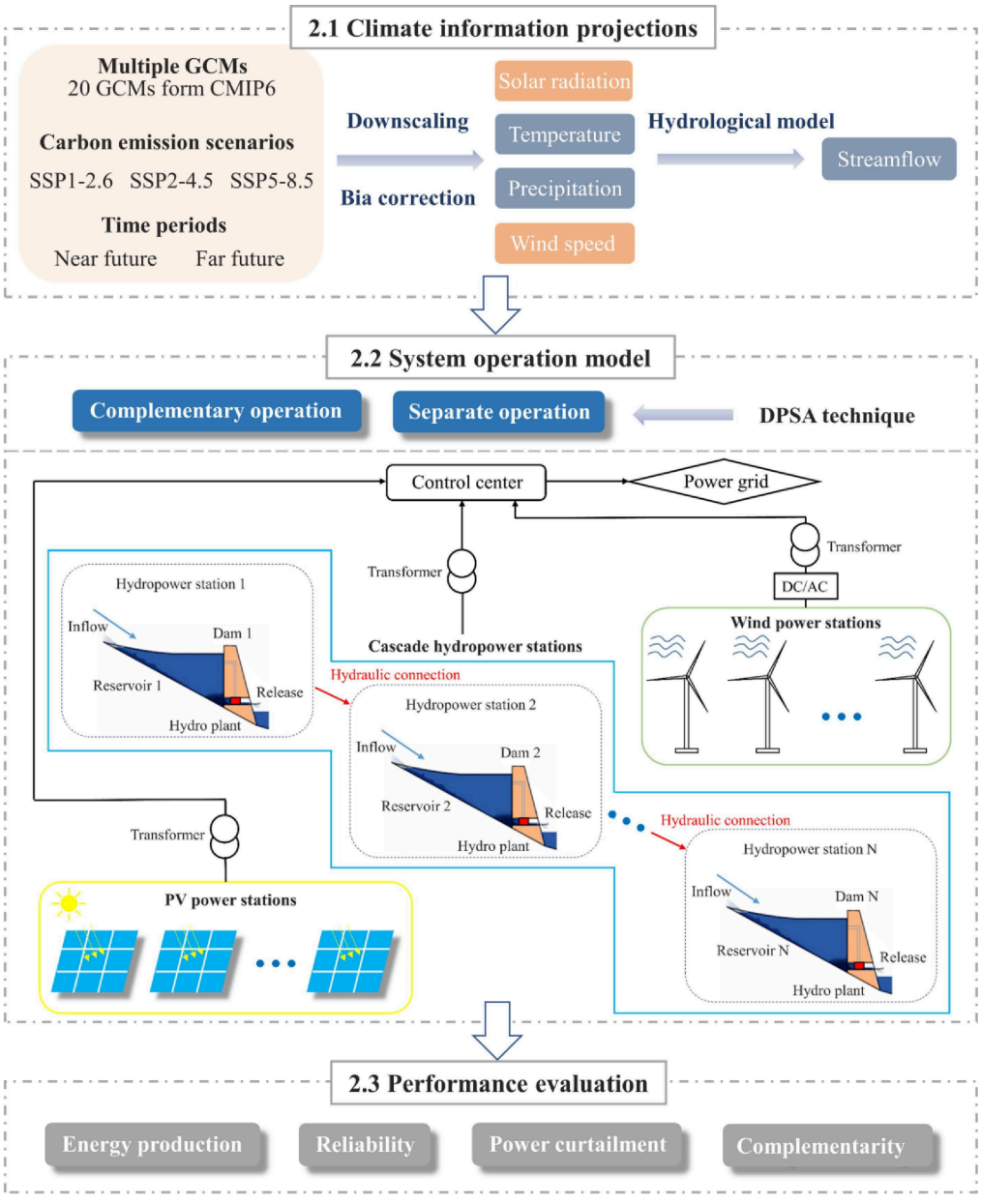


Figure 17. Evaluation framework for a wind–photovoltaic–hydro complementary system [70].

For simulation training, coordinated dispatch should extend beyond an optimization module that produces a single solution. The platform should generate alternative dispatch schemes under different wind, photovoltaic, hydrological, load, and grid conditions, reproduce the corresponding system responses, and enable operators to compare their effects

on reliability, economy, renewable-energy accommodation, and operational risk. In this context, optimization and evaluation models serve not only as decision-support tools but also as mechanisms for scenario construction and strategy comparison.

Accordingly, coordinated-dispatch training can be organized as a closed process of scenario generation, multi-energy optimization, system-response simulation, scheme evaluation, and operator decision-making. Such a process allows operators to examine how hydropower regulation, renewable-energy variability, system constraints, and dispatch strategies interact under different operating conditions, thereby shifting dispatch training from passive observation of optimization results toward active comparison and decision-making.

4.4. Operator Training and Assessment

Operator training is the main function that differentiates a simulation-training platform from conventional monitoring and visualization systems. Existing virtual simulation studies indicate that digital environments can support equipment operation, procedural training, fault handling, and standardized assessment while avoiding the operational risks associated with training directly on physical systems [138]. For hydro–wind–photovoltaic centralized control, however, training requirements are more complex because operators must simultaneously process heterogeneous information from multiple stations, interpret alarms and operating trends, execute dispatch instructions, and coordinate different energy resources.

Training scenarios therefore need to reproduce realistic operator–system interactions, including monitoring-information acquisition, control-command execution, alarm response, operating-mode switching, and coordination among different energy stations. Routine operations, remote-control procedures, alarm handling, cross-station coordination, and typical fault diagnosis can be incorporated into scenario libraries. In practice, however, constructing representative scenarios is not straightforward. Operating conditions vary considerably across stations and energy sources, while rare or compound events may have limited historical records. Scenario design must therefore balance operational realism, coverage of critical situations, and appropriate training difficulty rather than simply increasing the number of predefined cases.

Operator behavior analysis provides a basis for extending training from task completion toward quantitative competency assessment. Command sequences, response times, alarm-confirmation processes, operation paths, and corrective actions can be recorded to identify misoperations, omissions, delayed responses, and decision-making weaknesses. Based on these records, performance can be assessed in terms of procedural compliance, response efficiency, alarm-handling accuracy, decision quality, and coordination capability. Procedural compliance reflects whether actions follow predefined operating requirements; response efficiency characterizes the timeliness of operator actions; alarm-handling accuracy evaluates the correctness of fault recognition and response; and coordination capability reflects the ability to manage interactions among multiple energy sources and stations. The practical difficulty lies in converting these heterogeneous behavioral records into reliable measures of operator competency. The relative importance of response time, procedural correctness, decision quality, and coordination performance may vary with scenario type and operating severity, and a single fixed scoring rule may not adequately distinguish between acceptable alternative responses. Assessment criteria and weighting schemes therefore require calibration against expert knowledge, operating procedures, and representative training cases.

Accordingly, operator training can be organized as a closed process of scenario execution, behavior recording, performance evaluation, error tracing, and replay-based

improvement. The effectiveness of such a closed-loop mechanism depends not only on the completeness of recorded behavior but also on the validity and consistency of the assessment criteria. Establishing reproducible scenario libraries and validated competency-evaluation methods is therefore an important prerequisite for moving simulation training from procedural demonstration toward systematic operator development.

4.5. Emergency Drills

Emergency drills extend routine training to abnormal, rare, and high-risk conditions that are difficult or unsafe to reproduce in real systems. In hydro–wind–photovoltaic centralized control, emergencies may involve extreme hydrological conditions, rapid renewable-energy fluctuations, equipment faults, communication failures, protection actions, and changing dispatch constraints. These disturbances may interact across stations and energy types, requiring training scenarios to reproduce not only individual faults but also fault propagation and multi-event coupling.

Dynamic simulation enables the evolution of such events to be reproduced through changes in equipment states, alarms, power balance, regulation resources, and system risk, allowing operators to compare different response strategies. Fault analysis, intelligent alarming, and assisted decision-making technologies [139] can further support scenario diagnosis and response guidance. However, constructing credible compound-fault scenarios remains challenging because rare emergencies provide limited historical data, and interactions among equipment, protection, communication, hydrological, and renewable-energy processes are difficult to model comprehensively. Inaccurate fault or system-response models may therefore reduce the realism and training value of the simulated scenarios.

Emergency-drill assessment can consider fault-identification time, alarm judgment, command execution, handling completeness, system recovery, and risk containment. Combined with process replay, these indicators can reveal weaknesses in operator behavior and emergency procedures. Nevertheless, emergency response does not always have a single optimal sequence of actions; different strategies may be acceptable depending on system conditions and available regulation resources. Evaluation should therefore consider both procedural compliance and the resulting system response rather than relying only on predefined action sequences. Overall, the development of emergency-drill functions requires more than expanding the number of predefined fault cases. Representative scenario construction, credible fault-evolution modeling, and validated response-assessment criteria are central to ensuring that emergency drills reflect realistic multi-energy operating risks.

5. Research Gaps and Future Challenges

5.1. Multi-Energy Modeling and Simulation

Simulation training platforms have gradually evolved from basic equipment representation toward more complex operational-process reproduction and fault scenario simulation. Nevertheless, existing models are still predominantly developed for individual energy systems or specific application scenarios, and comprehensive representation of hydro–wind–photovoltaic centralized-control processes remains insufficient. The difficulty mainly originates from the heterogeneous dynamic characteristics of different energy sources. Hydropower involves hydraulic processes, reservoir regulation, and cascade interactions, whereas wind and photovoltaic generation exhibit strong variability caused by meteorological uncertainty. Therefore, achieving unified simulation of multi-energy coupling, cross-station coordination, and dynamic operating evolution remains challenging. Moreover, increasing model complexity and spatial coverage can substantially increase computational demand, making it difficult to maintain both high fidelity and real-time performance when multiple stations and energy sources are simulated simultaneously. Future

development therefore needs to balance model accuracy, computational efficiency, and real-time requirements while improving the integration of physical mechanisms, data-driven methods, and operational data.

5.2. Digital-Twin Application

Digital-twin technology has expanded the connection between physical systems and virtual environments through continuous data exchange and model updating, with energy-sector applications gradually extending from state monitoring to prediction, fault diagnosis, and decision support. However, most existing implementations remain focused on operational analysis, while digital twins specifically developed for comprehensive operator training are still limited. For hydro–wind–photovoltaic centralized-control training, the digital twin must support not only equipment-state representation but also continuous synchronization of multi-station operating conditions, abnormal-event reproduction, and interactive operator response. In practice, this synchronization can be affected by communication latency, missing or abnormal measurements, inconsistent sampling intervals, and other field-data quality issues, which may introduce discrepancies between physical operating states and their virtual representations. Therefore, a key challenge is to maintain reliable physical–virtual consistency under imperfect operational data while preserving the real-time interaction required for training. Improving data-quality management, synchronization mechanisms, and model-updating strategies will be essential for advancing digital twins from monitoring-oriented applications toward reliable training-oriented platforms.

5.3. Operator Assessment

Simulation training platforms have become an important approach for reproducing operating procedures, equipment states, and fault scenarios without affecting actual power-system operation. At present, however, the majority of studies concentrate on scenario construction and operation practice, whereas systematic evaluation of operator competency has received comparatively less attention. For centralized-control operators, training effectiveness depends not only on whether predefined tasks are completed but also on response efficiency, alarm interpretation, decision-making processes, and coordination capability under complex multi-energy conditions. Conventional evaluation methods based mainly on operation results cannot fully capture these aspects. Developing assessment approaches that incorporate operational behavior, response characteristics, and decision-making processes will therefore be essential for improving the objectivity and effectiveness of operator training.

5.4. Cybersecurity and Data Trustworthiness

The increasing connection of operational data, communication networks, and digital models has expanded the functional capability of digital-twin-based simulation training platforms. Meanwhile, this integration also introduces new requirements regarding data security, communication reliability, and trustworthiness of virtual representations. In hydro–wind–photovoltaic centralized-control training, potential risks may arise from abnormal data transmission, unauthorized access, and inconsistencies between physical and virtual states. Existing digital-twin studies mainly emphasize monitoring, prediction, and optimization functions, while security mechanisms specifically designed for training-oriented applications remain insufficiently explored. Future platform development should incorporate secure data exchange, access control, anomaly detection, and reliable physical–virtual interaction mechanisms to improve the credibility and practical applicability of simulation environments.

5.5. Interoperability and Engineering Validation

The implementation of hydro–wind–photovoltaic centralized-control simulation training platforms requires coordination among heterogeneous devices, simulation models, communication systems, and operational databases. A remaining challenge is that differences in data structures, communication protocols, and modeling environments continue to restrict the integration and scalability of such platforms. Meanwhile, comprehensive system-level validation of existing digital-twin-based training platforms under realistic centralized-control conditions remains limited. Issues, including consistency between simulation models and actual systems, real-time performance under complex scenarios, and effectiveness of training outcomes, need additional evaluation. Strengthening standardized interfaces, modular architectures, and validation through real-time simulation, hardware-in-the-loop testing, and field operational data will be important for improving their engineering applicability.

6. Conclusions

With the large-scale integration of renewable energy, hydro–wind–photovoltaic centralized control is evolving from conventional monitoring and unified management toward multi-energy coordination, intelligent dispatch, and decision support. This review summarizes the development of centralized-control systems, simulation training technologies, and digital-twin applications for hydro–wind–photovoltaic centralized control. The main conclusions are as follows:

1. The reviewed studies show that centralized-control systems for hydropower, wind power, and photovoltaic power have developed relatively mature architectures and fundamental operational functions. Hydropower centralized control mainly emphasizes water–power coordination, reservoir regulation, and cascade dispatch, whereas wind and photovoltaic systems focus more on generation forecasting, condition monitoring, and intelligent operation and maintenance. Their integration into hydro–wind–photovoltaic centralized control enables multi-source information sharing, cross-station coordination, and complementary operation. However, existing centralized-control systems are primarily designed for production operation and provide limited support for operator training, fault drills, and emergency scenario reproduction.
2. The review indicates that existing power simulation training platforms have achieved important progress in equipment modeling, operational process reproduction, and fault-scenario simulation. However, most current platforms remain oriented toward individual plants, single-energy systems, or specific training tasks, with limited capability for reproducing complex hydro–wind–photovoltaic centralized-control processes. Meanwhile, digital-twin technology provides technical support for physical–virtual mapping, dynamic state synchronization, and model-based analysis, but its application in comprehensive operator-oriented training remains at an early stage.
3. Taking an actual hydro–wind–photovoltaic centralized-control system in a river basin as the engineering basis, this review develops a digital-twin-based simulation training framework by incorporating existing simulation-training technologies and digital-twin concepts. The framework integrates multi-energy dynamic simulation, centralized monitoring and coordinated dispatch, abnormal-scenario reproduction, operator interaction, training assessment, and emergency drills to support the reproduction of complex operating processes. However, the fully integrated framework still requires further system-level validation to verify its real-time performance and engineering applicability.
4. Future research on hydro–wind–photovoltaic centralized-control simulation training platforms should further improve the realism and practical applicability of multi-

energy simulation. As system scale and complexity increase, models need to reproduce hydropower regulation, cascade interactions, and wind–photovoltaic variability with sufficient fidelity while maintaining real-time performance. Reliable physical–virtual synchronization and realistic abnormal-event reproduction also remain important under communication delays, incomplete or abnormal field data, and limited records of rare events. In addition, operator-training effectiveness should be supported by assessment methods covering procedural compliance, response efficiency, decision quality, and coordination capability. Further validation of simulation training platforms is also needed to strengthen their reliability and applicability in practical centralized-control environments.

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