Intelligent, Secure, Sustainable, and Scalable Control of Renewable Energy in Smart Grid: A Review on Forecasting, Optimization, and Coordination Frameworks

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Manuscript submitted October 11, 2025; accepted November 10, 2025; published December 4, 2025.
doi: 10.12720/sgce.14.2.40-62

Abstract: The rapid integration of variable Renewable Energy Sources (RES) into power systems demands control strategies that are scalable, privacy-preserving, and cyber-resilient. This review synthesizes recent advances in forecasting, optimization, and coordination frameworks relevant to Distributed Energy Resources (DERs), emphasizing three core findings: (i) distributed multi-agent approaches combined with model-predictive and learning-based controllers provide the most promise for scalable real-time coordination, (ii) federated and edge-cloud learning paradigms substantially reduce data-sharing requirements but require stronger adversarial defenses and standardized interfaces, and (iii) a persistent gap exists between simulation results and field-level validation, particularly for forecast–control co-design and cybersecurity-by-design. We present a novel taxonomy that organizes methods by control architecture and computational foundation, a comparative evaluation framework to assess scalability and resilience, and a conceptual, modular architecture to guide future experimental deployments. Finally, we identify prioritized research directions—explainable Artificial Intelligence (AI), federated Multi-Agent Systems (MAS), regulatory co-design, and large-scale testbeds—aimed at closing the research-to-deployment gap.

Keywords: smart grids, Model Predictive Control (MPC), Artificial Intelligence (AI), Multi-Agent Systems (MAS), Federated Learning (FL), blockchain, cyber security, forecasting, Distributed Energy Resources (DERs), edge computing

1. Introduction

Climate change, the depletion of fossil fuel resources, and increasing geopolitical uncertainties have collectively accelerated the global transition toward sustainable energy systems. In this context, Renewable Energy Sources (RESs)—such as wind and solar power—have become essential components of modern power networks. According to recent forecasts, renewables are expected to account for more than 60% of global electricity generation by 2050 [1, 2].

Despite this promising outlook, the integration of RESs into existing grid infrastructures presents significant challenges due to their inherent variability and unpredictability. These challenges manifest across technical, economic, and operational dimensions [3–5].

Smart grids—digitally enhanced power systems supported by advanced Information and Communication Technologies (ICT)—have emerged as a viable solution to address these integration issues. By enabling bidirectional communication, decentralized control, and adaptive optimization, smart grids can enhance system reliability, efficiency, and flexibility [6, 7]. Nevertheless, the seamless incorporation of RESs within smart grid architectures is far from straightforward. It necessitates the adoption of advanced control methodologies and robust optimization frameworks capable of managing uncertainty, maintaining system stability, and ensuring economically efficient energy dispatch under stringent operational constraints [8, 9].

Conventional power grid architectures and control strategies were not originally designed to accommodate large-scale penetration of Renewable Energy Sources (RESs). Centralized control schemes, in particular, often suffer from scalability limitations and communication bottlenecks when managing distributed generation units. Moreover, the inherent intermittency and unpredictability of solar irradiance and wind speed introduce significant uncertainty in power generation forecasting. Such variability can lead to voltage sags, frequency deviations, and potential economic losses [10, 11].

Although distributed and AI-driven control strategies are gaining increasing attention, few existing frameworks holistically integrate forecasting, control, and cybersecurity within a unified, field-validated architecture. This paper addresses this critical gap by proposing a comprehensive and cyber-resilient control framework that synergistically combines these dimensions.

Furthermore, while several optimization techniques have been developed for specific applications, many fail to effectively handle the multi-objective, multi-scale, and cyber-physical complexities inherent in modern smart grids. For instance, single-layer optimization approaches are often inadequate for coordinating power generation, storage systems, and dynamic loads in hybrid renewable environments. The lack of interoperability among Distributed Energy Resources (DERs) further exacerbates these coordination and control challenges [12–14].

The control and optimization challenges associated with renewable-integrated smart grids represent not only a technological concern but also a strategic imperative. Enhanced renewable integration serves multiple critical objectives: reducing carbon emissions through increased renewable penetration [15], strengthening operational resilience against demand fluctuations [16], enabling peer-to-peer energy trading and distributed ownership models, and improving overall economic efficiency by minimizing energy losses and optimizing dispatch operations [17, 18].

Recent advances in Artificial Intelligence (AI), Model Predictive Control (MPC), Multi-Agent Systems (MAS), and blockchain technologies have demonstrated considerable potential in addressing these challenges [19–21]. However, despite substantial progress, there remains a lack of comprehensive research that simultaneously considers the technical, economic, and cybersecurity aspects of renewable energy integration. Therefore, a unified and systematic approach is urgently needed to guide future research directions and enable practical, scalable implementations of next-generation smart grid systems.

Although the existing literature offers extensive research on individual algorithms and enabling technologies, several critical gaps remain unaddressed in the context of renewable-integrated smart grids. These gaps can be summarized as follows:

- Absence of Unified Frameworks: Most existing studies evaluate control and optimization approaches in isolation, focusing on technical, economic, or cybersecurity aspects separately. Comprehensive frameworks that holistically integrate these dimensions within a unified architecture remain scarce in the literature [22, 23].
- Scalability and Interoperability Challenges: While decentralized control architectures offer promising flexibility, they often face scalability limitations and interoperability issues arising from heterogeneous communication protocols and diverse device capabilities [24, 25].
- Inadequate Cybersecurity Considerations: Many optimization and control models overlook cyber-physical vulnerabilities, leaving systems susceptible to threats such as spoofing, data tampering, or Denial-of-Service (DoS) attacks [26, 27].

- Lack of Real-World Validation: A considerable number of proposed techniques remain confined to simulation or laboratory environments, lacking validation through Hardware-in-the-Loop (HIL) testing or field-level implementation [3, 12, 28].
- Suboptimal Utilization of Artificial Intelligence (AI): Despite the substantial potential of AI-driven methods, many models exhibit limited interpretability, generalizability, and robustness under dynamic operating conditions. This restricts their practical deployment in real-world smart grid applications [19, 27, 29].

This review contributes to the growing body of smart grid research by systematically synthesizing methods and frameworks across forecasting, optimization, and secure coordination. The key contributions are outlined below:

1. Novel Taxonomy of Control and Optimization Frameworks: Develops a comprehensive taxonomy that categorizes forecasting and control approaches according to control architecture (centralized, decentralized, distributed) and computational foundation (MPC, RL, ML, metaheuristics, hybrid methods). This taxonomy synthesizes heterogeneous literature into an accessible structure for comparative evaluation.

2. Comprehensive Thematic Synthesis: Provides a thematic literature synthesis that collates and contrasts empirical findings across forecasting, optimization, and secure coordination, with emphasis on relative performance, typical datasets, and common validation practices.

3. Critical Gap Analysis: Conducts a critical gap analysis that identifies areas of limited coverage—most notably forecast-control co-design, cybersecurity-by-design, and field-level validation—and prioritizes research targets.

4. Evaluation Framework: Presents a comparative evaluation framework and visual synthesis (tables and matrices) that benchmark approaches across scalability, convergence, resilience, and real-world readiness - enabling readers to select candidate approaches depending on their operational constraints and validation resources.

5. Conceptual Framework for Future Research: Proposes a modular conceptual architecture that combines forecasting, predictive control, and distributed coordination through federated learning and multi-agent systems (federated edge–cloud MAS with MPC and learning-based forecasting). This framework is presented as a guide for future research and deployment, rather than a validated operational system.

Together, these contributions advance the understanding of intelligent and cyber-secure control in renewable-integrated smart grids by linking theory, emerging technologies, and open research directions within a unified conceptual foundation.

Highlights:

- Integrated AI-based framework for forecasting, optimization, and coordination
- Comprehensive taxonomy and analysis of smart grid control strategies
- Handling cybersecurity using federated learning and blockchain technologies
- Importance of forecast-control integration for real-time systems

2. Literature Review

This section presents a structured overview and classification of existing research on control schemes and optimization methods for integrating solar and wind power into smart grids. The discussion is organized around several key thematic areas:

(i) Control architectures (centralized, decentralized, and distributed),

(ii) Model Predictive Control (MPC) and hierarchical optimization methods,

(iii) Artificial Intelligence (AI) and Machine Learning (ML) approaches,

(iv) Heuristic and metaheuristic techniques,

(v) Multi-Agent Systems (MAS) and blockchain technologies,

(vi) Uncertainty modeling and forecasting, and

(vii) Hybrid renewable energy system optimization.

Each theme is analyzed in detail, supported by relevant technical explanations, representative equations, and schematic illustrations where appropriate.

2.1. Control Methodologies

2.1.1. Centralized control

Centralized control represents the traditional approach employed in conventional grid management systems. In this architecture, supervisory functions, data acquisition, dispatch operations, and control commands are managed under a single, central authority. This configuration enables effective coordination and global system observability, making it suitable for networks characterized by predictable generation patterns and limited variability [1, 5, 6].

However, centralized architectures inherently suffer from several drawbacks. They exhibit limited scalability and introduce single points of failure, which compromise system resilience. While centralized control can be effective for small-scale, homogeneous networks—where high-speed and reliable data communication is achievable—it becomes increasingly inefficient under high penetration of Distributed Energy Resources (DERs). Challenges such as communication latency, data congestion, and computational bottlenecks significantly restrict its applicability in large-scale, dynamic, and heterogeneous smart grid environments.

Mathematical Formulation:

In mathematical terms, for a central authority to dispatch operations on one system, including both generation and storage, we minimize the total operation cost:

$$\min_{P_g,P_s} C_g(P_g) + C_s(P_s) \tag{1}$$

subject to:

$$\begin{gathered} \sum P_g + \sum P_s = P_d \\ P_g^{min} \leq P_g \leq P_g^{max}, P_s^{min} \leq P_s \leq P_s^{max} \end{gathered} \tag{2}$$

where: $C_g(P_g)$, $C_s(P_s)$ depicts the cost of generation and storage; P_d is total demand and P_g is power generated from traditional or renewable sources; P_s is power discharged or charged from energy storage; P_g^{Min}, P_g^{Max} shows generation limits; P_s^{Min}, P_s^{Max} indicates storage charge/discharge.

2.1.2. Decentralized control

In decentralized control systems, each device or subsystem operates autonomously with its own local control logic, relying on limited or no centralized coordination. Communication is primarily localized, enabling each unit to make control decisions based on local measurements and operational states. Such architectures are inherently scalable and robust, offering resilience against single-point failures and adaptability to dynamic network configurations [22, 23].

However, decentralized control suffers from a lack of global optimality, as each controller optimizes only local objectives without a unified system-wide perspective. Consequently, during contingency events or abnormal grid conditions, decentralized controllers often fail to achieve coordinated responses, which can lead to suboptimal system performance and reduced operational stability.

2.1.3. Distributed control

Distributed control represents an evolution beyond the purely decentralized paradigm by incorporating cooperation and coordination among multiple agents through communication and consensus mechanisms. In this architecture, agents exchange information and negotiate control actions using algorithms such as consensus-based control, game theory, or distributed optimization, allowing for system-level coordination without centralized supervision [13, 18, 24].

This approach strikes a balance between scalability and coordination, leveraging local computations and peer-to-peer communications to achieve near-global optimality. Nonetheless, the performance of distributed control systems is highly dependent on the reliability of communication networks, synchronization accuracy, and the tuning of convergence parameters. Any degradation in communication stability can significantly affect convergence speed and system robustness, posing practical challenges in large-scale implementations.

For example, a popular consensus-based economic dispatch update rule adopted in distributed control is given as:

$$x_i(k+1) = x_i(k) + \alpha \sum_{j \in \mathcal{N}_i} \left[x_j(k) - x_i(k)\right] \tag{3}$$

where: $x_i(k)$ is decision variable of agent i at iteration k; N_i is the neighboring of agent i; and α is the consensus step size (positive constant).

A large variety of architectures – from centralized to distributed – has been proposed in the literature dealing with the variability and uncertainty of the RES. Their structural differences and implications for scale and robustness are depicted in Fig. 1 [3, 18, 24].

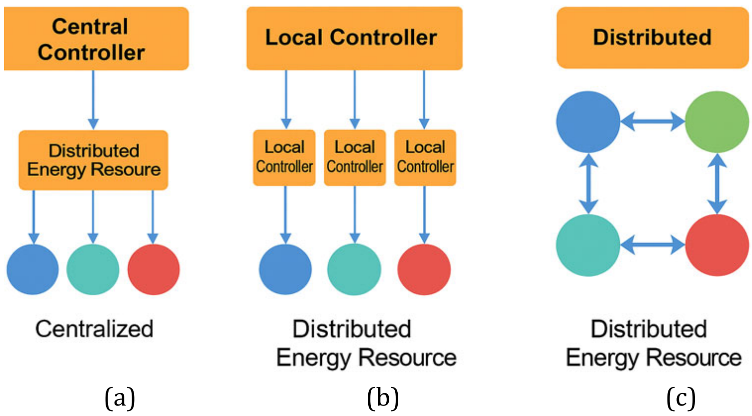

Fig. 1. Centralized, decentralized, and distributed control architectures in RES-integrated smart grids. (a) Centralized; (b) Decentralized; (c) Distributed.

This figure illustrates the structural differences among three major control paradigms. Centralized control features a single supervisory controller managing all DERs, decentralized control enables independent local decision-making, and distributed control allows cooperative coordination through inter-agent communication. Each architecture represents a trade-off among scalability, fault tolerance, and coordination complexity.

In the figure:

(a) Centralized control: One central controller is connected to several local units. Everything is based on a central node of data and decision-making.

(b) Decentralized Control: In which each node functions independently with no interconnection established if the quick local decision is required.

(c) Distributed control: All nodes communicate with the neighboring nodes only by a consensus algorithm or coordination algorithm without any central controller.

2.2. Model Predictive Control (MPC)

Model Predictive Control (MPC) has been extensively applied in smart grid systems to enable real-time optimization under operational and physical constraints. Owing to its predictive modeling capability, MPC can forecast system behavior and determine optimal control actions for various applications such as energy storage management, inverter control, and voltage stability enhancement [1, 7, 25]. The method's ability to handle multiple control variables simultaneously while explicitly considering system constraints makes it a powerful and flexible control strategy for dynamic and uncertain environments.

However, the performance of MPC is highly dependent on the accuracy of system models and the quality of forecasts used in prediction. Model mismatches or inaccurate forecasting of renewable generation (e.g., solar irradiance or wind speed) can significantly degrade its control performance and lead to suboptimal decisions.

In the context of building Heating, Ventilation, and Air Conditioning (HVAC) systems, MPC has been successfully utilized to optimize control actions over a finite prediction horizon. The main objective is to minimize deviations from the desired temperature trajectory while simultaneously reducing operational costs, ensuring that all system constraints—such as thermal comfort limits and actuator bounds—are satisfied. This example demonstrates MPC's versatility and effectiveness in managing multi-objective optimization problems within cyber-physical energy systems. A typical formulation is:

$$\min_{\{u_k\}_{k=0}^{N-1}} \sum_{k=0}^{N-1} \left[\|x_k - x_{\text{ref}}\|_Q^2 + \|u_k\|_R^2\right] \tag{4}$$

subject to:

$$\begin{gathered} x_{k+1} = Ax_k + Bu_k \text{ (System dynamics)} \\ x_{min} \le x_k \le x_{max} \text{ (State constraints)} \\ u_{min} \le u_k \le u_{max} \text{ (Input constraints)} \end{gathered} \tag{5}$$

where:

- x_k: State of the system at time step k (voltage, frequency, State of Charge (SOC) in %)
- u_k: Control Setpoint (inverter setpoints, Battery Energy Storage System (BESS) dispatch)
- x_{ref}: Reference trajectory
- Q, R: Weighting matrices which penalize states and deviation of inputs
- N: Prediction horizon length
- A, B: System matrices (linearized or estimated model)

Applications include:

- Energy storage management [1]
- Voltage regulation with inverter control [6]
- Optimal power flow for microgrids [25]

2.3. Artificial Intelligence (AI) and Machine Learning (ML)

AI-oriented methods are increasingly being adopted to improve both forecasting accuracy and advanced control capabilities in smart grid systems. Fig. 2 presents the taxonomy of optimization techniques, highlighting their classification and interrelation across various control and decision-making layers.

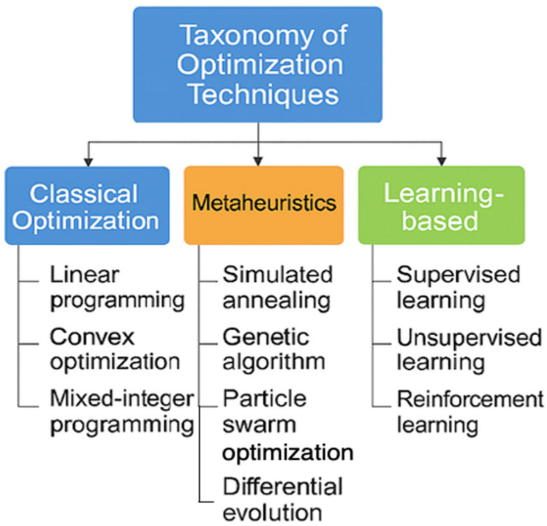

Fig. 2. Taxonomy of optimization techniques for smart grid control.

In Fig. 2, a hierarchical taxonomy categorizing optimization strategies used in renewable-integrated smart grids, including model-based (e.g., MPC), AI-based (e.g., RL, DL), and heuristic/metaheuristic methods (e.g., PSO, GA). The taxonomy highlights relationships among control paradigms and optimization algorithms.

2.3.1. Reinforcement Learning (RL)

Reinforcement Learning (RL) algorithms such as Deep Q-Network (DQN) and Proximal Policy Optimization (PPO) have shown promise in learning optimal dispatch strategies under dynamic and uncertain grid conditions [12, 14, 45]. RL can operate in nonlinear and time-varying environments with minimal prior knowledge. However, it requires large amounts of training data, carefully designed reward functions, and suffers from low interpretability due to its black-box nature.

Example: A standard reward function for RL-integrated smart grid control can be defined as:

$$R_t = -\left[\alpha(f_t - f_{\text{ref}})^2 + \beta(V_t - V_{\text{ref}})^2 + \gamma C_{\text{op},t}\right] \tag{6}$$

where: f_t is grid frequency at time t, V_t is voltage at the Point of Common Coupling (PCC); f_{ref} is nominal frequency (e.g., 50 Hz or 60 Hz); V_{ref} is nominal voltage (e.g., 1.0 p.u.); $C_{op,t}$ is operating cost (e.g., fuel cost, curtailment cost); α, β, γ are weight factors.

Their overall feedback architecture is illustrated in Fig. 3:

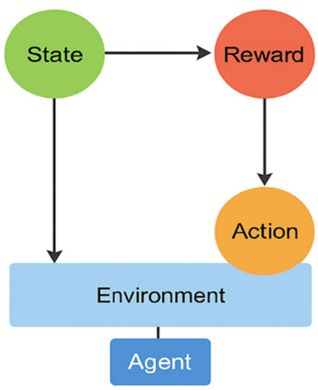

Fig. 3. Reinforcement Learning (RL)-based control loop in a smart grid.

Fig. 3. shows the closed-loop workflow of an RL-based controller in grid operations. The agent interacts with the environment by receiving system states (e.g., voltage, frequency), applying control actions (e.g., inverter dispatch), and updating policies through rewards.

2.3.2. Deep learning for demand forecasting

Deep learning models—including Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Convolutional Neural Network (CNN)-LSTM hybrids—generally outperform classical statistical techniques (Auto Regressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA)) and many traditional machine-learning regressors (e.g., SVR, Random Forest) in short-term forecasting of solar, wind, and load under high-resolution datasets [26, 27]. Reported error metrics vary significantly with dataset resolution, geographic diversity, prediction horizon, and pre-processing steps (e.g., denoising, feature engineering). Where available, hybrid CNN–LSTM architectures often show notable improvements in capturing spatio-temporal patterns compared with single-model baselines on the same dataset and pre-processing pipeline.

Compared to conventional approaches, deep learning models generally achieve lower Root-Mean-Square Error (RMSE) and Mean Absolute Error (MAE) under comparable datasets, reflecting their Superior capacity for learning complex patterns in renewable generation data. However, they require large, high-resolution datasets and involve significant computational overhead for training and deployment, especially when implemented at the edge.

Hence, while deep learning models deliver relative performance advantages in forecasting accuracy and adaptability, their effectiveness depends on data availability, training scalability, and integration with real-time control and decision-making layers.

2.4. Heuristic and Metaheuristic Optimization

Several metaheuristic algorithms, including Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Ant Colony Optimization (ACO), have been widely applied in optimizing hybrid renewable energy systems [2, 23, 26, 41].

2.4.1. Genetic Algorithms (GA)

GAs have been employed for optimal placement of Distributed Energy Resources (DERs) and energy storage sizing [2, 26]. They offer strong global search capabilities and can be easily hybridized with other optimization techniques.

2.4.2. Particle Swarm Optimization (PSO)

PSO has been extensively used for optimal reactive power dispatch and voltage stability enhancement due to its fast convergence and computational efficiency [23, 26, 40].

2.4.3. Ant Colony Optimization (ACO)

ACO has been explored for grid reconfiguration and communication routing in smart grid applications [26].

Comparison:

- GA: Strong global search ability and good hybridization potential, but relatively slow convergence.
- PSO: Fast convergence and computationally efficient, but prone to local minimum.
- ACO: Adaptive and suitable for routing problems, but sensitive to parameter tuning and less effective in high-dimensional optimization.

Although heuristic and metaheuristic methods are flexible and easy to implement, they lack guarantees of global optimality and may not be suitable for real-time control due to their stochastic convergence behavior [9, 21].

2.5. Multi-Agent Systems and Blockchain Integration

2.5.1. Multiple agents coordination

Multi-Agent Systems (MAS) enable decentralized decision-making through cooperative learning and consensus mechanisms. Each agent typically represents a Distributed Energy Resource (DER) or load and exchanges information with others to achieve global objectives [8, 13, 38]. Common applications include:

- Peer-to-Peer (P2P) energy trading.
- Demand-Side Management (DSM).
- Decentralized coordination of energy storage.

Robust, real-time multi-objective optimization can be achieved through consensus-based and game-theoretic algorithms [17].

2.5.2. Blockchain

Blockchain technology complements MAS by enabling secure, transparent, and tamper-resistant energy transactions [15, 49]. In P2P markets, smart contracts automate settlements while preserving privacy. To reduce computational burdens on edge devices, lightweight blockchain architectures such as Directed Acyclic Graph (DAG)-based frameworks are being explored [49].

2.6. Forecasting and Uncertainty Modelling

Several uncertainty modeling methodologies are employed to address the RES variability:

- Stochastic forecasting [28, 29]
- Scenario-based MPC [8]
- Robust optimization [16]

Stochastic Optimization: Stochastic optimization is one way to directly incorporate uncertainty into the objective and constraints by considering the relevant variables as random parameters [46]. A stochastic optimization model in general form is given by:

$$\min_{x \in X} \mathbb{E}_{\xi}[f(x, \xi)] \tag{7}$$

where: x is the decision variable; ξ is a random variable of forecasting error; $f(x, \xi)$ is the cost function depending on both decision and uncertainty; X is the set of feasible decisions (which is determined by the constraints of the system that we are dealing with); and E_{ξ} is the expectation operator across the probability distribution of ξ.

2.7. Optimization of Hybrid Renewable Systems

Computational tools dedicated to Hybrid Renewable Energy System (HRES) optimization are described in [14, 28, 47], including main solvers, platforms, and modeling environments. The operation strategy Hybrid systems (Solar + Wind + BESS) have very complicated control layers. Recent research has focused on integrating long-term economic planning with short-term scheduling and real-time control [10, 11, 30].

- Top layer: Long-term economic planning.
- Intermediate layer: Short-term scheduling and energy management.
- Bottom layer: Real-time voltage/frequency control.

Hybrid approaches (e.g., MPC + fuzzy control [10], GA + rule-based [11]) are commonly preferred for their adaptability in complex mixed-generation scenarios.

A brief comparison of the reviewed control and optimization techniques is given in Table 1, summarizing their major advantages, disadvantages and how they correspond to application suitability requirements in smart grid and RES integration.

Table 1. Overview over Control and Optimization Techniques with their Strengths, Weaknesses and Application Scenarios

Technique	Use Case	Strengths	Limitations	Real-Time Suitability	References
MPC	Voltage control, BESS, OPF	Handles constraints, predictive	Needs accurate models	High	[1, 6, 25]
Reinforcement Learning (RL)	Adaptive dispatch, Demand Response (DR)	Learn from interaction	Data-hungry, black-box behavior	Medium	[12, 14, 45]
Heuristics (GA, PSO, ACO)	Scheduling, Voltage/VAR control (VAR), DER sizing	Global search, easy implementation, adaptive	Slow, suboptimal for real-time, sensitive	Low-Medium	[2, 23, 26]
MAS	DER coordination, DSM	Scalable, decentralized intelligence	Needs coordination protocols	High	[13, 17, 24]
Blockchain	P2P markets, secure trading	Secure, auditable transactions	Latency, scalability in dense grids	Medium	[15, 47]

2.8. Summary and Gaps

Although the optimization and control in smart grids integrated with RESs have been well studied, the following gaps need to be highlighted.

- Lack of co-design of forecast control in a real-time application.
- Field validation is fairly limited; most techniques are available for simulation only.
- Limited integration of FL and MAS for edge intelligence.
- Underutilized application of blockchain with DAG-based consensus: Low-latency P2P energy trading.

These gaps are driving the unified control framework that is proposed in this work. In Table 2, two proposed techniques are presented, along with their validation for real-time and field testing in solar, wind and energy trading applications.

Table 2. Overview of the Validation Level (Real-time and Field-Testing Status) and Study Scope

Study	Technique	Scope	Real-Time Capability	Field Validation
[27]	CNN-LSTM Forecasting	Solar & Wind	✗	✗
[7]	Blockchain for P2P	Energy Trading	✓	✓

To address this challenge, we propose a unified architecture that integrates deep learning, predictive control, and distributed coordination, aiming to bridge the gap between forecasting and control in distributed renewable energy systems.

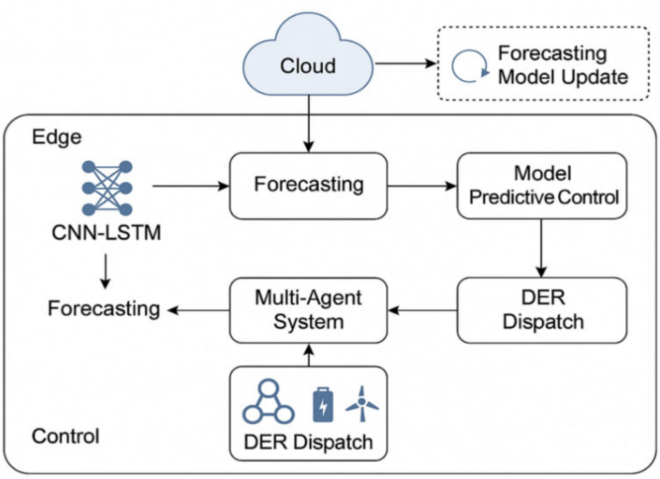

Fig. 4. Unified forecast–control architecture for distributed energy resources (conceptual framework).

Fig. 4 illustrates the proposed architecture comprising forecasting, optimization, and coordination within a federated edge–cloud framework. At the edge, a CNN-LSTM model predicts solar or load profiles, which feed into a Model Predictive Control (MPC) layer for setpoint tuning. Distributed Energy Resource (DER) dispatch is coordinated through Multi-Agent Systems (MAS) across the network. In the cloud, federated learning refines forecasting models securely without sharing raw data, ensuring adaptive and privacy-preserving intelligence at edge nodes. Although conceptual, this architecture reflects real-world scenarios and serves as a reference for deployment and validation.

3. Technological Trends and Challenges of Future Development

The integration of Renewable Energy Sources (RES) into smart grids presents multifaceted challenges involving technical, computational, cybersecurity, and regulatory dimensions. Emerging technologies such as Artificial Intelligence (AI), edge computing, and blockchain are creating new opportunities for advancement, yet they also introduce added layers of complexity.

3.1. Technical Difficulties for RES Integration

3.1.1. Source variability and intermittency

The major challenge with solar and wind power lies in the uncertainty of their generation profiles. Although forecasting techniques using deep learning models—such as LSTM and CNN hybrids—have shown improvement [26, 27], rapid fluctuations can still cause voltage sags or swells, frequency excursions, and even load shedding or RES curtailment [6, 23]. Integration barriers remain significant, including the absence of harmonized standards and limited control responsiveness [44].

3.1.2. Grid inertia deficiency

High penetration of inverter-based RES reduces the grid's inherent inertia, leading to rapid frequency deviations and poor transient damping [3, 11].

Proposed solutions include:

- Virtual synchronous machines for inertia emulation [25]
- Fast-responding Battery Energy Storage Systems (BESS) for synthetic inertia and damping [10]

3.2. Computational and Optimization Issues

3.2.1. Multi-Objective (MO) optimization

Modern smart grids must balance multiple conflicting objectives, including:

- Cost minimization
- Emission reduction
- Power quality (voltage, frequency, THD)
- Reliability and resiliency

Multi-objective evolutionary algorithms (MOEA) and Pareto-based optimization approaches [2, 17, 23] are widely used; however, their real-time deployment is limited by high computational demand.

3.2.2. Scalability and latency in a distributed environment

Consensus Algorithms distributed control systems are weak against latency due to:

- Dense communication networks
- Latencies of edge-device computation
- Reliability of the wireless link [13, 18]
- This is important in high-DER environments (e.g., smart cities), where millisecond counts for stability.

Impact of Consensus Delay: The convergence rate and stability of the consensus-based algorithms can be seriously affected by communication delays in distributed MAS. When there is a time delay in communication between agents, the update rule is further adjusted for latency:

Equation:

$$x_i(t+1) = x_i(t) + \alpha \sum_{j\in\mathcal{N}_i} \left(x_j\left(t-\tau_{ij}\right) - x_i(t)\right) \tag{8}$$

where: $x_i(t)$ is state/control variable of agent i at iteration t; τ_{ij} delay between agents i, j; N_i set of neighboring agents of node i; and α is consensus step size.

3.3. Cybersecurity and Privacy

3.3.1. Cyber-physical attack surfaces

With the infusion of AI, Internet of Things (IoT), and Blockchain technologies into the smart grid, a series of novel threats arise at the cyber-physical interface. Such attacks are often carried out through:

- False Data Injection (FDI): It is known that compromised sensor readings may have an adverse effect on forecasting and optimization accuracy [14].
- Denial of Service (DoS): Flooding based attacks on communication channels to break the real time control loops.
- Model Poisoning: In the context of AI based control, training data can be maliciously manipulated to cause unsafe grid behavior [17, 37].

To address these challenges, standardized approaches to cybersecurity frameworks must be embraced. Notably:

- International Electrotechnical Commission (IEC) 62351: Specifies communication protocols that securely “control and monitor” power systems.
- National Institute of Standards and Technology (NIST) SP 800-82: Provides a guide for Industrial Control Systems (ICS) cybersecurity.
- ISO/IEC 27019: Adapts general information security control objectives and controls to the energy utility information security environment.

Such vulnerabilities and their corresponding defense mechanisms could be mapped into a multi-layer threat model, as depicted in Fig. 5.

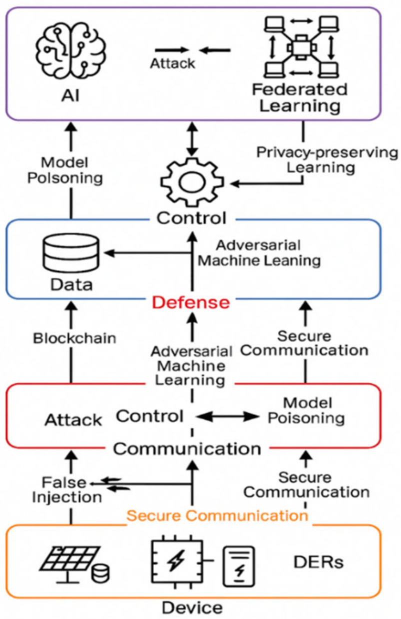

Fig. 5. Cybersecurity threat model for smart grid control systems.

Fig. 5 depicts a multi-layer representation of vulnerabilities and defense mechanisms across device, communication, control, and AI layers. Attack vectors include false data injection, denial-of-service, and model poisoning, while mitigation measures involve blockchain, secure protocols, and privacy-preserving learning. We reveal vulnerabilities and weaknesses at those four layers: (i) Device and DER layer, (ii) Communication layer, (iii) Control and Data layer, and (iv) AI and federated learning layer. Defense approaches are based on blockchain, security communication protocols, and privacy-preserving federated learning.

By incorporating these requirements into the design and validation process of AI- and MAS-based smart grid solutions, compliance with and resilience from contemporary threat landscapes are accomplished.

3.3.2. Data privacy in decentralized energy markets

The information exchange involved in P2P trading and decentralized optimization on energy consumption, pricing and location data may raise privacy concerns. Although blockchain provides secure transaction logging, tamper-resistance [8, 9] (amongst other security guarantees), but these must be combined with lightweight encryption, anonymization, and privacy-preserving AI techniques e.g., federated learning.

3.4. Recent Technological Trends

3.4.1. Edge and fog computing

Delegating control and optimization to local or regional nodes (fog/edge) reduces latency and enhance system resilience:

- Edge: Local decision and actuation
- Fog: Regional collection and optimization
- Cloud: Global learning and coordination

This three-layered structure in Fig. 6 enhances fault-tolerance and also permits real-time adaptive control [12, 13, 38, 42].

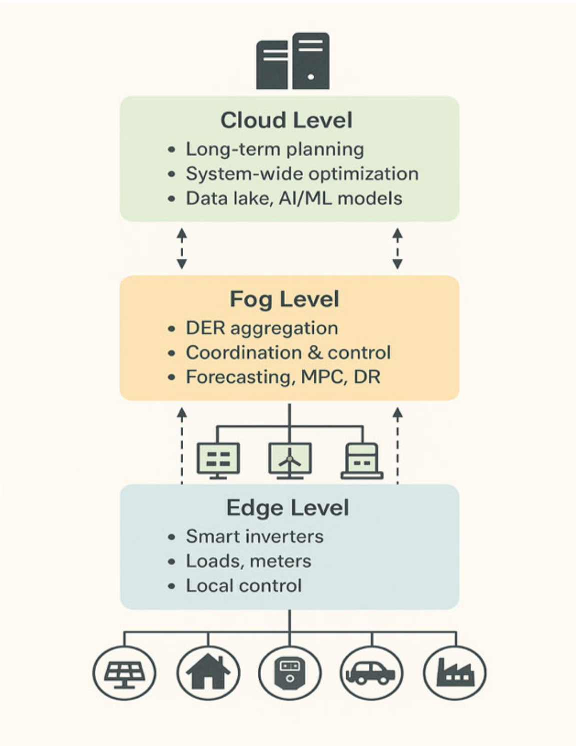

Fig. 6. Three-Level control framework for Distributed Energy Resources (DERs).

Fig. 6 illustrates the interaction among edge, fog, and cloud layers in hierarchical control. Edge handles local sensing and actuation, fog enables regional coordination, and cloud provides global optimization and learning. This framework enhances scalability and resilience for distributed smart grids.

3.4.2. Federated Learning (FL)

Federated Learning (FL) allows edge devices to collaboratively train shared AI models without sharing raw data, thus ensuring privacy and reducing bandwidth usage. This approach is particularly suitable for distributed smart grid systems that handle sensitive user information [12, 14].

Workflow Example:

- Local DERs develop models with their own data.
- Only model gradients are communicated to a central aggregator.
- Distributed model is then sent back to DERs.

$$\theta_t^{(i)} = \theta_{t-1}^{(i)} - \eta \nabla L_i \left(\theta_{t-1}^{(i)}\right) \tag{9}$$

where: $\theta_t^{(i)}$: Locally trained model at a client i after finishing its local SGD updates for round t; $\theta_{t-1}^{(i)}$: model parameters at the previous training step; η: the learning rate (or step size); and $\nabla L_i(\theta_{t-1}^{(i)})$: the gradient of the local loss function L_i with respect to the model parameters at step $t-1$.

Averaged at the central place:

$$\theta_t = \sum_{i=1}^{N} \frac{n_i}{n} \theta_t^{(i)} \tag{10}$$

Here: θ_t: Global model parameters at communication round t after aggregation; n_i: number of training data sample at client i; n: Total number of samples at all clients.

Advantages:

- Data stays local
- Reduces privacy risk
- Facilitates learning together for DERs

3.5. Policy and Regulations Challenges

3.5.1. Non-standardization in communication protocols

The lack of standardized communication protocols across Distributed Energy Resources (DERs), Electric Vehicles (EVs), and inverters creates integration difficulties and limits interoperability. Diverse control interfaces hinder plug-and-play functionality [18, 19, 38]. Although standards like IEEE 2030.5 and OpenADR are progressing, adoption remains inconsistent across regions.

3.5.2. Market architecture for distributed energy

Defining flexible pricing mechanisms, aggregator roles, and real-time trading structures is crucial for enabling decentralized, transaction-based markets [8, 9, 43]. Without a clear framework, DER participation remains economically unattractive.

3.6. Sustainability and Life-Cycle Management

Integrating RES sustainably requires battery degradation [10], embodied energy in power electronics, and end-of-life recycling for solar panels and wind blades [30, 31]. True sustainability demands circular design principles and effective recycling strategies beyond mere operational efficiency.

While several technologies reviewed show promise, real-world deployment remains limited. Companies like Siemens and ABB have demonstrated federated learning for predictive maintenance and anomaly detection [11, 12]. Similarly, blockchain-based pilots such as Power Ledger (Australia), TenneT (Germany), and SP Group (Singapore) explore peer-to-peer energy trading. However, scalability, interoperability, and regulatory uncertainty still constrain widespread implementation.

3.7. Future Directions

We make the following observations in Table 3, based on the above challenges and trends, with respect to prioritizing research directions:

Table 3. Priority Research Directions for Scalable Smart Grid Control

Future Research Direction	Description	Key References
Cyber-resilient control systems	Co-design cybersecurity features within optimization and control layers	[14, 17, 37]
Explainable AI (XAI)	Improve interpretability of deep learning models for grid control and anomaly detection	[50, 51]
Grid-forming inverters	Enhance voltage/frequency stability via inverter-based virtual synchronous machines	[3, 11]
Federated/Decentralized Optimization	Achieve scalable and privacy-preserving intelligence at the edge	[11, 12, 16, 18]
Regulatory Co-design	Develop market mechanisms and policies aligned with decentralized control and trading models	[8, 9, 31]
Real-World Testbeds	Validate proposed architectures using hardware-in-the-loop and live field deployments	[1, 10, 28, 39]

4. Comparative Analysis and Research Gaps

This section provides a comparative summary of state-of-the-art optimization and control methods across key dimensions, including control architecture, optimization approach, forecasting model, coordination strategy, and integration framework. It also outlines current research gaps and offers perspectives for future advancements in this field.

4.1. Comparative Evaluation of Control Methodologies

The control framework for renewable energy system control strategies can be mainly divided into centralized, decentralized and distributed paradigms. A summary of the key papers is included below in Table 4:

Table 4. Centralized, Decentralized and Distributed Approach Control Architecture Comparison

Reference	Control Type	Scalability	Resilience	Coordination	Implementation Level
[2, 18, 19]	Centralized	✗	✗	✓	Pilot-scale
[20, 21]	Decentralized	✓	✓	✗	Real-time feasible
[12, 16, 17]	Distributed (MAS)	✓✓	✓✓	✓✓	Simulation/Field trials
[3, 10]	Grid-forming	✓	✓✓	✓	Demonstration
[7, 8]	Blockchain-aided	✓✓	✓	✓✓	Experimental

Observation: Although distributed control demonstrates the most sustainable performance, only a few studies [7, 8, 16] report real testbed validation, indicating a significant gap between research and practical deployment. Among the available approaches, distributed multi-agent systems stand out for their scalability, resilience, and coordination capabilities, making them most aligned with the proposed framework in both architecture and implementation.

4.2. Optimization Methods: Comparative Depth

The reviewed studies utilize various optimization techniques tailored to specific grid objectives, including economic dispatch, loss minimization, voltage regulation, and resiliency enhancement. The most commonly adopted optimization categories are summarized in Table 5.

Table 5. Comparison of Optimization Methods in Smart Grid Control

Technique	Strengths	Limitations	Cited Papers
Linear/Quadratic Programming (LP/QP)	Fast, convex guarantees	Limited to linear models	[18, 21]
Mixed-Integer Programming (MIP)	Binary states modeling	Computationally expensive	[2, 24]
Heuristics (GA, PSO)	Flexible, global search	No guarantee of optimality	[9, 21, 24]
MPC	Predictive; constraint-aware	Requires accurate models	[1, 6, 23]
Reinforcement Learning (RL)	Adaptive, real-time capable	Complex training, black-box behavior	[11, 13]
Multi-Objective Evolutionary Algorithms (MOEA)	Handles trade-offs (Pareto front)	Slow convergence	[2, 31]

Observation: Although hybrid approaches such as MPC + RL [14, 48] and GA + Fuzzy [10, 11] show strong potential for real-time and scalable smart grid optimization—particularly in scenarios involving uncertainty and dynamic DER behavior [6, 23]—their practical implementation remains very limited [8, 39]. While numerous optimization algorithms have been proposed [47], only a few integrate real-time control and forecasting capabilities [14, 28].

A comparison of the key methods and techniques discussed in the reviewed literature is presented in Table 6.

Table 6. Summary Matrix of Main Smart Grid Control Methodologies

Feature / Technique	Centralized	Decentralized	Distributed (MAS)	AI-Based	MPC	Heuristics
Scalability	✗	✓	✓✓	✓	✗	✓
Resilience	✗	✓	✓✓	✓	✓	✗
Real-time Capability	✗	✓	✓	✓	✓	✗
Learning Ability	✗	✗	✓	✓✓	✗	✗
Data Dependency	✗	✗	✓	✓✓	✓	✗
Cited References	[18, 19]	[16, 20]	[12, 17]	[11, 25]	[1, 6]	[2, 24]

Note: Symbol Legend: ✓✓ - Strongly supported; ✓ - Partially supported; ✗ - Not supported

Table 6 summarizes various control methods based on key performance criteria. Decentralized and AI-enabled approaches exhibit notable advantages, including high scalability, robustness, and adaptive learning capabilities. In contrast, centralized methods generally show less competitive results. Heuristic methods, while simple, lack real-time adaptability and remain static. Overall, the comparison highlights the strengths of distributed and AI-driven systems, particularly when integrated with forecasting models and coordination mechanisms such as Multi-agent Systems (MAS).

4.3. Forecasting and Uncertainty Estimation

Accurate prediction of renewable energy generation is vital for maintaining grid stability. Only a few studies [11, 27] have considered forecast uncertainty alongside Real-Time Control (RTC). Stochastic and robust MPC approaches remain limited to specific applications [6, 14]. A comparison of commonly used forecasting models is presented in Table 7 below:

Table 7. Prediction Accuracy of Statistical and AI Models for Solar, Wind and Load data

Model Type	Method	RMSE (kW)	MAE (kW)	R^2 Score	Data Type	Reference
Statistical	ARIMA	18.7	14.2	0.83	Solar Photovoltaic (PV) (1-min data)	[4, 32]
	SARIMA	17.3	13.1	0.85	Wind speed (10-min)	[19]
	Exponential Smoothing	20.4	15.8	0.78	Load (hourly)	[33]
Machine Learning	Support Vector Regression (SVR)	13.2	10.5	0.89	PV output (5-min)	[34]
	Random Forest	11.9	9.1	0.91	Wind + solar (mixed)	[6, 14]
Deep Learning	LSTM	8.6	6.7	0.95	Solar irradiance (1-min)	[26, 27]
	CNN-LSTM Hybrid	7.3	5.8	0.96	Wind power (10-min)	[11, 35]
	GRU	9.1	7.2	0.94	Load forecast (5-min)	[36]

As shown in Table 7, deep learning models—particularly CNN-LSTM hybrids—consistently outperform traditional statistical and classical machine learning models in forecasting solar, wind, and load data. These models achieve lower RMSE and MAE values and higher R^2 scores, indicating superior accuracy and generalization. However, their practical deployment is limited by high computational demands and the need for high-resolution input data. Federated Learning (FL) and edge–cloud collaborative frameworks offer promising solutions to address these challenges by preserving data privacy and optimizing computational resource allocation.

4.4. Coordination and Integration in the Energy Market

Decentralized energy markets—such as Transactive Energy Systems (TES) and Peer-to-Peer (P2P) trading—are gaining significant attention for enabling local energy exchange and improved grid flexibility. Table 8 summarizes selected studies that apply Multi-Agent Systems (MAS) and blockchain technologies to coordinate these decentralized markets, highlighting their architecture, applications, and key outcomes.

Table 8. Examples of MAS and Blockchain Integrations in Energy Markets

Reference	Coordination Layer	Incentive Mechanism	Scalability
[7]	MAS + Blockchain	Tokenized P2P trading	High
[8]	Smart Contracts	Dynamic pricing	High
[12]	Game Theory	Nash equilibrium	Moderate

Decentralized energy exchange, supported by multi-agent coordination and blockchain-enabled transactive markets, shows great potential for large-scale distributed energy trading. However, its practical deployment depends on the advancement of regulatory frameworks and the resilience of underlying cyber-infrastructures [15].

4.5. Validation and Deployment Gaps

Despite the growing adoption of AI-based and decentralized control strategies for smart grids, most studies remain limited to simulation-based validation. Real-world implementations are rare and typically restricted to laboratory-scale prototypes or Hardware-in-the-Loop (HIL) setups. Table 9 categorizes the validation techniques identified across the reviewed literature.

Table 9. Reviewed Papers on Validation Techniques in Smart Grid Systems

Validation Level	Examples	Remarks
Simulation-only	[Most papers]	Often use standard IEEE test networks; lack real environmental variables
Hardware-in-the-loop	[1, 3, 10, 11, 16, 28]	Typically limited to small-scale or single-function validation
Field deployment	[8, 23, 39]	Very few studies demonstrate operational readiness in real-world scenarios

Key Remarks: Only a few studies, such as Refs. [8, 39], demonstrate full-scale deployment incorporating blockchain-based trading or distributed control. Most existing works rely on idealized simulations that exclude critical real-world factors such as noise, communication delays, regulatory compliance, and cyber-attacks. Therefore, advancing toward Hardware-in-the-Loop (HIL) testing and pilot-scale implementations is essential to validate the robustness and reliability of AI-driven and decentralized control strategies under realistic operating conditions.

4.6. Research Gaps and Open Problems

According to the comparative analysis, we highlight the following open research challenges in Table 10.

Table 10. Research Gaps and Suggested Solution Approaches

Gap	Needs	Suggested Approach
Lack of Unified Control Frameworks	Multi-layer co-design	Hybrid MPC + LSTM + RL [11]
Weak Forecast-Control Integration	Joint design of models and controllers	[22, 24]
Lack of Cybersecurity-by-Design	Integrated threat models	Blockchain + Xplainable Artificial Intelligence (XAI) [15]
Poor Scalable Optimization	Lightweight algorithms for edge	FL + MAS [11, 16]
Regulatory Misalignment	Market-compatible frameworks	Dynamic pricing [7, 8]
Limited Deployment Validation	Large-scale testbeds	HIL + pilot trials [1, 10]

A layered research gap map is depicted in Fig. 7, which visually summarizes the identified gaps in terms of forecasting, control, cybersecurity, and validation.

	None	Partial	Full
Forecasting		**[4, 6, 19, 27]**	**[11, 12]**
Control		**[2, 16, 18]**	**[1, 6, 12]**
Security		**[14, 37]**	**[15]**
Filed Deployment	**Most Studies**	**[10, 28, 39]**	**[1, 11, 12]**

Fig. 7. Research gap map for smart control of decentralized renewable energy systems.

Here, a matrix visualization maps research coverage across four key domains—forecasting, control, cybersecurity, and validation. The shaded regions highlight persistent gaps, including weak forecast–control integration, limited cybersecurity-by-design, and insufficient field validation. The rows represent the main functional layers (Forecasting, Control, Security, and Field Deployment), while the columns indicate the level of research coverage: None, Partial, and Full. Shaded cells denote areas requiring further attention, and the accompanying references point to studies that partially or fully address each respective domain.

According to the comparative analysis, three gaps are being identified as particularly urgent for the future. First, no integrated forecast-control architecture has been developed, and prediction models are not tightly embedded into control loops, making real-time and efficient adaptation impossible. Second, the lack of field-level validation among the majority of the reviewed studies makes the operational utility of proposed solutions questionable; practically all examined solutions that rely only on simulation do not include latency, hardware variability, and communication delay. Third, cybersecurity is, in general, an underexplored dimension, and in decentralized and AI-based systems adversarial threats and privacy loss might undermine grid stability. Overcoming these limitations is crucial to building robust, scalable, and reliable smart grid infrastructures to accommodate high renewable energy integration.

5. Future Work

There are several promising research directions that can bridge the gap between conceptual design and practical deployment of smart grid solutions. The key areas for future work include:

- Forecast–Control Co-Design: Develop unified architectures that tightly integrate AI-based forecasting with adaptive control to enhance responsiveness and robustness [14, 22].
- Federated Intelligence and MAS Integration: Explore federated learning–enabled multi-agent architectures for improved privacy, scalability, and coordination in edge-dominated networks [11, 12, 16].
- Interpretable and Robust AI: Implement explainable and adversarial-resilient AI models (e.g., XAI + FL) to ensure transparency, trust, and safety in real-time decision-making [14, 27, 41, 50].
- Cybersecurity and Attack-Resistant Design: Adopt standardized threat models and secure communication protocols (e.g., IEC 62351, NIST SP 800-82) for resilient optimization and control frameworks [14, 17, 37].
- Regulatory and Market Integration: Develop adaptive control and policy frameworks to enable dynamic pricing, Peer-to-Peer (P2P) energy trading, and aggregator-based market participation [8, 9, 31, 39].
- Field-Level Validation: Emphasize Hardware-in-the-Loop (HIL), digital twin, and pilot-scale field testing to capture real-world communication delays, hardware variations, and cyber-physical interactions [1, 10, 28, 39].

By addressing these directions, future research can advance the development of robust, interoperable, and scalable smart grid ecosystems that fully leverage the potential of renewable energy integration.

6. Conclusion

This review presents a comprehensive overview of the state-of-the-art in smart grid control, emphasizing the integration of advanced forecasting, optimization, and coordinated control strategies. By categorizing control schemes into centralized, decentralized, and distributed architectures, it highlights their respective strengths and limitations in the context of Hybrid Renewable Energy (HRE) integration. Among these, decentralized Multi-Agent Systems (MAS) demonstrate the highest potential for scalable and real-time coordination.

Optimization approaches such as Model Predictive Control (MPC), Reinforcement Learning (RL), and metaheuristics each offer distinct advantages—MPC provides robustness under strict constraints, while RL adapts effectively to dynamic and uncertain conditions. Deep learning-based forecasting models, particularly CNN-LSTM architectures, outperform traditional statistical models in accuracy but face deployment challenges due to their high computational demand. MAS and blockchain frameworks are gaining traction for secure, decentralized coordination and Peer-to-Peer (P2P) energy trading; however, real-world deployment remains limited.

Despite notable progress, key challenges persist. Forecasting and control modules are often decoupled, reducing real-time efficiency. Most reported approaches lack physical validation or testing under realistic, adversarial conditions. Furthermore, cybersecurity concerns in AI-driven and federated systems, coupled with non-standardized communication protocols, continue to hinder interoperability and large-scale adoption. Addressing these gaps through harmonized standards, resilient control design, and real-world testbed validation will be vital for achieving reliable, secure, and sustainable smart grid operation.

Conflicts of Interest

The author declares no conflicts of interest.

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