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AI-Enabled Smart Grid: Integrating Electrical Power Systems, Computer Intelligence, and Wireless Communication Technologies

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Abstract
The transition of conventional electrical networks into smart, flexible, and reliable energy systems requires more than digitalizing individual grid elements. Modern power systems comprise renewable energy sources, distributed resources, electric vehicles, smart meters, storage systems, smart substations, and controllable consumers. These grid assets produce vast amounts of heterogeneous data that need reliable communication infrastructure for appropriate utilization in day-ahead scheduling, real-time monitoring, control, and maintenance. This study focuses on electrical power systems, artificial intelligence (AI), edge-cloud computing, and wireless communications in the context of AI-enabled smart grids. An integrated research approach was undertaken by surveying the state-of-the-art methods in power system operation, machine learning, communication networks, interoperability, edge intelligence, and cybersecurity. Particular emphasis was put on unifying power and communication infrastructures through cross-layer concepts applied in the AI-enabled smart grid framework. The framework includes power, sensing and devices, communication, edge-intelligence, cloud-intelligence, and application/control layers interconnected via continuous cyber-physical feedback. The role of AI algorithms, including machine learning, deep learning, reinforcement learning, federated learning, anomaly detection, and digital twins was evaluated in power forecasting, renewable energy prediction, grid fault diagnosis, voltage control, demand response, maintenance, electric vehicle management, and cybersecurity. The communication-related aspects of the smart grid framework were examined by considering the requirements of 5G, WiFi, LPWAN, wireless mesh networks, fiber, and hybrid communication systems. The study concluded with recommendations on how power systems should transition from separate optimization of energy, computation, and communication domains towards communication-aware AI and grid-aware networking. Edge intelligence, federated learning, interoperability, quality of service adaptation, and cyber-secure control were identified as five key enablers of future smart grids. The study provides a cross-disciplinary insight into the design of next-generation communication-integrated smart energy systems.

Keywords: Smart grid; artificial intelligence; machine learning; electrical power systems; wireless communication; 5G; edge computing; renewable energy; distributed energy resources; cybersecurity.

Introduction

The electricity power networks undergo paradigm changes from centralized and unidirectional to distributed and interactive forms, utilizing a growing quantity of data and cyber-physical systems. Electricity networks used to be mostly unidirectional, carrying electricity from large-scale generators through the transmission system and the distribution system to final consumers. Today's networks comprise a broader range of elements: photovoltaic, wind power, battery storage, electric vehicles, microgrids, controllable loads, smart meters, smart devices, and prosumers.

A smart grid, therefore, cannot be regarded only as an upgraded electric grid. It is an integrated system, in which the electric infrastructure, sensors, communications, computers, control systems, and algorithms function together. The US Department of Energy defines smart grid technologies as those that allow for two-way communication and advanced control and computational capabilities, to help manage power grids by using equipment, such as phasor measurement units, smart meters, automated relays, feeder switches, and energy storage. The National Institute of Standards and Technology defines smart grid, meanwhile, as a coordinated set of electrical, information, communication, and computational capabilities covering the generation to the end-use of electricity.

This transformation is being accelerated by a rapidly increasing penetration of renewable-energy sources, such as solar and wind generation. Although these are environmentally attractive sources, they are two-sided: their power outputs may fluctuate rapidly and be only partially predictable and controllable. The growing number of electric-vehicle (EV) chargers represents another source of power demand that, with vehicle-to-grid operation, can become a distributed energy resource. Meanwhile, millions of smart meters, sensors, and other devices are generating data at different rates and of varying criticality.

Artificial intelligence can be applied to interpret these data. For instance, machine learning enables the discovery of associations between electricity use and various factors. In addition, such methods as deep learning ensure the analysis of non-linear processes and spatio-temporal dynamics. Moreover, reinforcement learning approaches can address control and optimization tasks. Computer vision is applicable to inspecting infrastructure, while anomaly detection algorithms can reveal irregularities in electricity or telecommunications. The recent studies emphasize that federated learning, digital twins, generative AI, and artificial-intelligence-of-things solutions can be integrated into future smart grids.

However, intelligent computation cannot be separated from communication infrastructure. A highly accurate control algorithm has little value if sensor information arrives too late at the controller. In contrast, very fast communication has minimal value if the resulting information is not converted into meaningful operational decisions. Smart-grid performance therefore depends on a three-way interaction among electrical system behaviour, communication network behaviour, and computational intelligence.

The IEEE/IEC ecosystem seems to be gradually shifting towards this. IEC 61850 has evolved to embrace not only substation automation, but also broader power-utility automation and information exchange needs for intelligent electronic devices and distributed-energy applications. NIST also promotes interoperability among generation, transmission, distribution, distributed-energy resources, operations, markets, and customers.

Although a substantial amount of research has been conducted, the majority of the existing literature tackles artificial intelligence, power-system optimization, communication networks, and cybersecurity as isolated domains. This is an impractical approach since the smart grid is considered to be a cyber-physical system. Hence, this study aims to introduce a cross-layer framework in which electrical, intelligence, and communication aspects are jointly taken into account.

Electrical system behaviour <-> communication network behaviour <-> computational intelligence

Research Objectives

The purpose of this research is to devise an integrated conceptual and technological framework for an AI-based smart grid that utilizes the combined abilities of power system operation, computer intelligence, and wireless communication.

The specific goals are: To characterize the emerging needs from the operations of electric power systems with high penetration of renewables, distributed generation, and electric vehicles; To characterize the needs and opportunities for artificial intelligence and machine learning in grid operation, monitoring, prediction, protection, control, and optimization; To analyze and compare emerging wireless and hybrid communication technologies for different smart-grid applications; To formulate a cross-layer AI-enabled smart grid framework that integrates grid operation, communication, and computer intelligence; To analyze interoperability, latency, reliability, scalability, security, and privacy; and To identify research challenges for developing smart grids that are autonomous, communication-aware, and cyber-secure.

Research Questions

The main objective of the study is defined by five research questions, namely: RQ1: How can artificial intelligence contribute to the monitoring, forecasting, protection, and control of modern electrical power systems? RQ2: What communication technologies are promising for different applications of smart grids? RQ3: How can the constraints of the electrical system and the communication network be considered in artificial intelligence-based grid decision-making? RQ4: How can edge computing and federated learning help reduce latency and ensure safety when dealing with distributed energy information? RQ5: What technical and cybersecurity challenges should be resolved to operate AI-based smart grids in a large-scale, fully autonomous manner?

Background and Related Research

Evolution from Conventional Grid to Smart Grid

The conventional electricity grid is centralized and has limited exchange of information between utilities and consumers. Monitoring is focused on the main generation and transmission facilities, and less on the distribution and the consumers.

Smart grids allow sensing and control throughout the energy network, including advanced metering infrastructure that enables information about consumption, phasor measurement units that provide synchronized electrical measurements, intelligent electronic devices that allow control, and distributed-energy-resource controllers that coordinate distributed generation and storage.

As such, the grid becomes a closed loop cyber-physical system:
Measure -> Communicate -> Analyse -> Decide -> Control -> Re-measure
The effectiveness of each stage influences the subsequent ones. For example, faulty sensors provide false information, communication delay decreases the value of timely measurements, inadequate analytical models make bad decisions, and delayed control action can reduce grid stability.

Artificial Intelligence in Power Systems

Artificial intelligence is no longer a novelty but rather an integral component in smart energy management systems. The study of integrated systems covers the problems of monitoring, diagnostics, optimization, energy management, microgrids, and virtual power plants within the context of smart grids.

AI methods related to smart grids include

AI Technique	Smart-Grid Application	Operational Benefit
Linear/ensemble ML	Load and price forecasting	Better scheduling
Artificial neural networks	Nonlinear prediction	Improved forecasting
CNN	Fault and signal classification	Automated diagnosis
LSTM/GRU	Time-series forecasting	Renewable/load prediction
Autoencoders	Anomaly detection	Early abnormality identification
Reinforcement learning	Grid control	Adaptive decision-making
Multi-agent RL	DER and microgrid coordination	Distributed control
Federated learning	Distributed model training	Increased privacy
Computer vision	Asset inspection	Automated maintenance
Digital twins	Grid simulation and prediction	Real-time virtual representation

Final thoughts: AI is most valuable in cases where analytical models are challenging to design because of huge dimensionality, uncertainty, or highly non-linear dependencies.
On the other hand, purely data-driven models have their share of shortcomings, too. First of all, the training data may not include rare failures, topological changes, or points of operation. The model may generalize poorly on data that follows a different distribution, or it may be deceived by artificial features planted in the input data. Therefore, one should not rely on such a model blindly; instead, it should be used in conjunction with a traditional physical power-system model.

Wireless Communication Technologies for Smart Grids

Communication requirements of the grid functions may vary drastically. For example, billing information may tolerate seconds or minutes of delay, but a protection or a fast automation scheme may involve communication with extremely low latency and high reliability. ITU's smart-grid guidance recognizes that some deterministic control applications may require communication latency of less than 10 ms and reliability of around 99.999%. It shows that the best-effort type of networking is not sufficient for some critical grid control applications.

5G Cellular Communication

5G is especially attractive due to its capacity to handle high device densities, high data rates, low delays, and network slicing. Different logical network slices could theoretically be allocated to smart-metering traffic, video inspection, operational monitoring, and critical control.
5G's potential applications include: distribution automation; DER monitoring; electric-vehicle charging; mobile workforce communication; drone-based inspection; smart metering; and microgrid coordination.
Multi-access edge computing can place computation close to 5G access networks, decreasing the distance between measurement acquisition and AI decision-making. ITU guidance specifically recognizes edge computing as a way to reduce bandwidth communication requirements and delays in smart-grid applications.

Wi-Fi and Wireless Local Area Networks

Wi-Fi enables very high throughput at relatively low deployment cost and can be used in buildings, industrial facilities, microgrids, and home energy–management systems. Nevertheless, interference, congestion, coverage limitations, and nondeterministic access make Wi-Fi less suitable for extremely critical protection functions without additional engineering controls.

LPWAN Technologies

Low-Power Wide-Area Network technologies can be applied in cases when a device needs to send limited amounts of data over great distances. Examples of such technology application are remote meter reading, monitoring of condition of transformers, environmental sensing, low-priority asset tracking, or monitoring of rural distribution networks. The main benefits of such technology are the possibility to cover large areas and low power consumption; however, the amount of data that can be transferred using these technologies is limited, and the latency is high, which rules out the use of these technologies for applications that require high-speed data transfer.

Wireless Mesh Networks

Mesh communication uses relays through neighboring nodes which can offer alternate routes for communication. Such redundancy is particularly useful for advanced metering infrastructure but introduces delays due to the multi-hop nature of the transmission. Also, security and routing policies are more involved.

Hybrid Wired-Wireless Architecture

It is important to note that no single communication technology is optimal for the electricity grid. Fibre offers high capacity and reliability for backbone communication, while wireless networks offer flexibility and cost-effective last mile connectivity. The recent ITU work on fibre to the power grid also emphasizes high bandwidth optical infrastructure and wired and wireless access mechanisms for modern power grid applications. Thus, the most practical architecture is generally hybrid.

Grid Function	Preferred Communication Approach
Protection and substation automation	Fibre / deterministic Ethernet
Wide-area monitoring	Fibre + cellular backup
Distribution automation	Fibre / 5G / RF mesh
Smart metering	RF mesh / cellular / LPWAN
Home energy management	Wi-Fi / Zigbee / similar PAN
EV charging	5G / Wi-Fi / wired Internet
Remote sensors	LPWAN / cellular
High-resolution inspection video	5G / fibre

Proposed AI-Enabled Cross-Layer Smart Grid Framework

The major contribution of this research is the proposed AI-Enabled Cross-Layer Smart Grid Framework (AI-CSGF). Instead of separating electrical engineering, computing, and communication functions, AI-CSGF contains six interacting layers.

Layer 1: Physical Power Layer

This layer represents the actual electricity system. The physical layer is governed by electrical variables such as voltage, current, frequency, active power, reactive power, and power quality. The layer includes conventional generation; renewable generation; transmission lines; substations; distribution feeders; transformers; battery storage; microgrids; electric vehicles; controllable loads; and prosumers.

Layer 2: Sensing and Device Layer

This layer transforms the physical grid behavior into digital information. In addition, it executes the commands coming from the top layer to the bottom layer through various physical devices. This layer consists of Phasor Measurement Units (PMUs), smart meters, intelligent electronic devices, protection relays, sensors connected to transformers, weather sensors, IoT nodes, EV charging controllers, and inverter controllers among others.

Layer 3: Communication Layer

The communication layer carries measurements and control information from the previous layers. Rather than being a passive pipe for data, the proposed framework takes into account communication-network conditions as part of grid intelligence. The framework includes fibre optics; Ethernet; 4G/5G; Wi-Fi; LPWAN; RF mesh; power-line communication; software-defined networking; and network slicing.

Layer 4: Edge Intelligence Layer

The edge layer deals with time-critical information near substations, microgrids, feeders, or electric vehicle charging stations. Edge AI is critical for the reason that constantly sending each and every measurement to some faraway cloud for processing creates unwelcome delays and bandwidth consumption. Edge AI includes local fault classification; detection of voltage anomalies; coordination of inverters; local prediction of demand; estimation of equipment health; detection of cyberattacks; and making emergency islanding decisions.

Layer 5: Cloud and System Intelligence Layer

The cloud or control-centre layer performs more computationally intensive and system-wide tasks. For this reason, an AI architecture based on a distributed edge-cloud is preferable to a fully centralized one. Long-term load forecasts; forecasts of renewable generation; digital-twin simulations; analytic market functions; maintenance scheduling; fleet-level analysis of EVs; model training; system-wide optimal power-flow calculations; and data analytics are some of the functions that can be related to this category.

Layer 6: Application and Control Layer

This layer comprises systems that enact intelligence into action. Applications of these systems are automatic generation control; economic dispatch; volt/VAR optimization; demand response; distributed energy resource

(DER) dispatch; battery management; EV charging; fault restoration; congestion management; and predictive maintenance.
Important network variables that can be estimated in the communication layer are:
N_t = {L_t, B_t, Rlink_t, J_t, P_t}

where L_t = communication latency; B_t = available bandwidth; Rlink_t = link reliability; J_t = jitter; P_t = packet-loss probability.

5. Cross-Layer Intelligent Decision Model

A distinctive characteristic of the proposed framework is that the AI controller does not consider electrical measurements alone. At time t, the system state can be represented as:
S_t = [G_t, D_t, R_t, E_t, C_t, A_t]

where G_t = grid operating state; D_t = electricity demand; R_t = renewable-generation state; E_t = energy-storage/EV state; C_t = communication-network state; A_t = asset-health and anomaly state.
The AI decision engine determines an action:
a_t = pi(S_t)
where pi represents the learned or hybrid intelligent control policy.
A general optimization problem may be formulated as:
J = w1 P_loss + w2 V_dev + w3 C_energy + w4 T_comm + w5 R_risk + w6 E_curt

Where Ploss is network power loss; V_dev is voltage deviation; C_energy is operating cost; T_comm is communication delay penalty; R_risk is reliability/cybersecurity risk; E_curt is curtailed renewable energy; w1. w6 represent operational priorities.
This formulation is different from standard optimization approaches in that it explicitly encodes communication performance into the operational decision. For instance, an AI controller may normally operate under a remote optimization command; however, if network latency increases, the controller could automatically shift to a safe local edge-control policy as opposed to waiting for a delayed remote command.

Research Methodology

The study adopts an integrative review and architecture-design methodology rather than presenting fabricated operational data. The research process consists of five stages.
Stage 1: Technology identification: The existing technologies were grouped into three major areas: power-system technologies, artificial intelligence and computational technologies, and communication and networking technologies.
Stage 2: Functional mapping: The technology items were related to major smart-grid functions, such as monitoring, forecasting, protection, control, optimization, maintenance, cybersecurity, and demand-side management.
Stage 3: Cross-layer requirement analysis: The power-system applications were compared based on the required levels of latency, reliability, computation, bandwidth, privacy, scalability, explainability, and resilience.
Stage 4: Architecture development: The functions derived from the cross-layer analysis informed the design of the six-layer AI-CSGF architecture.
Stage 5: Research-gap analysis: The research landscape and standard documents were examined to identify the major impediments in the practical realization of the smart grid.
This method is appropriate for this research because the aim is not to perform a field deployment but to assemble and critically evaluate a technically sound integrated framework.

Major Applications of the Proposed Architecture

Intelligent Load Forecasting

Electricity demand varies hourly, seasonally, by weather, customer behavior, and economic factors. An AI can extrapolate electricity demand by cross-referencing time, weather patterns, and historical trends.
Load_t = f(Time, Weather, HistoricalLoad, Price, Events)
Short-term forecasts are valuable for unit commitment, storage control, demand response, and energy trading. Fast local prediction can be provided at the edge level, based on a neighborhood or feeder model, while regional forecasts can be produced at the cloud level.

Renewable-Energy Forecasting

Solar and wind uncertainty increases balancing requirements. With the help of AI models, it becomes possible to utilize the information contained in past generation data together with meteorological observations, satellite or weather forecasts, and recent generation to improve forecasts. The ability to forecast renewable generation allows utilities to make decisions on reserves, curtailing, battery scheduling, and market participation more efficiently.

Intelligent Fault Detection and Self-Healing

Traditional protection generally reacts to events which have passed. AI allows other information which could indicate potential problems to be analysed, either before or during a disturbance. This information could include current waveform, voltage waveform, harmonics, relay information, temperature, vibration and communication problems. The engine can determine the type and location of any faults. Subsequently, following protection logic verification, automated switches can isolate the affected section and restore electricity from other available feeders if the network allows.

Predictive Maintenance

Electrical equipment heretofore may generally be maintained periodically or on failure. Predictive maintenance contemplates utilizing equipment condition information to anticipate equipment degradation. With respect to transformer condition monitoring, an equipment health index conceptually may be defined as:

HI = f(T_oil, T_winding, Gas, Vibration, Load, Age)

AI can identify unusual combinations of these variables and prioritize maintenance before catastrophic failure.

Demand Response

A cloud-based demand response system can be utilized in order to identify flexible customers to either lower or shift consumption over a certain period of time. Rather than simply communicating a price signal, the system can estimate expected demand, consumer flexibility, renewable supply, storage status, congestion levels, and communication availability. Afterwards, the system can organize flexible appliances, loads, and storage.

Electric Vehicles as Intelligent Grid Resources

The EV scale is both a challenge and an opportunity. Uncoordinated EV charging can lead to local peaks in electricity demand. AI coordinated EV charging has the potential to spread out the electricity needs on a large scale, but still meet the requirements of the drivers of these electric vehicles.

min sum_t (C_t P_t + lambda Peak_t)

subject to:

SOC_departure >= SOC_required

The controller seeks to minimize the cost of energy and peak demand while simultaneously ensuring that the required vehicle state of charge is achieved. Bidirectional vehicle-to-grid systems offer an additional dimension. The EV battery may be used to supply local demand, provide ancillary services or supply emergency power, while taking into account battery degradation and user preferences.

Edge AI and Federated Intelligence

Centralized AI requires data to be transferred to a central server. This creates three problems: communication overhead, privacy exposure, and dependency on network connectivity. Federated learning provides an alternative. Suppose N substations possess local datasets D1, D2, ..., DN. Each site trains:

theta_i^(t+1) = Train(theta^t, D_i)

Rather than transmitting the entire local dataset, the site transfers a model update to a coordinating platform. The global model can then be aggregated:

theta^(t+1) = sum_i [|D_i| / sum_j |D_j|] theta_i^(t+1)

This approach can help to decrease the amount of raw operational information that may be shared directly. The study discusses federated artificial intelligence as a key concept in the context of decentralized smart-grid cybersecurity and anomaly detection with specific attention to challenges related to communication overhead, device heterogeneity, non-independent and identically distributed data, and adversarial manipulation. Therefore, it is important to note that federated learning should be regarded as a privacy-enhancing model rather than an inherently private and secure solution.

Digital Twin Integration

A digital twin is used to represent the physical system and is constantly updated. In AI-CSGF, the digital twin is supplied with real-time information from the grid and holds a virtual model of the topology, generation, demand, equipment condition, voltage, and frequency in the network, as well as the status of distributed energy resources. Before applying a high-impact AI control action to the physical grid, the control centre can evaluate the action within the digital twin. The sequence becomes:

Physical Grid -> Sensors -> Digital Twin -> AI Prediction -> Safety Evaluation -> Control Command -> Physical Grid

This mechanism could potentially act as a safety layer between autonomous decision-making by AI and critical infrastructure. Current smart-grid AI research is already suggesting digital twins as an increasingly viable approach to cyber-physical modeling, simulation, and intelligent control.

Interoperability

One of the major challenges associated with smart-grid integration is interoperability. A utility may manage multiple manufacturers' equipment that utilizes different data models, communication protocols and technologies. IEC 61850 is critical because it defines standardized information models and communication concepts for power-

utility automation and intelligent electronic devices. The standard has evolved significantly and now extends well beyond substation automation towards broader utility and DER applications.
The proposed framework therefore advocates that AI platforms should not utilize proprietary device-specific data structures. A semantic interoperability layer should be implemented to allow the translation of heterogeneous device information into standardized machine interpretable representations. This enables the intelligence layer to comprehend not only that a value is 230, for example, but also that this may indicate voltage, its unit, location, time stamp, operating condition and quality.

Cybersecurity of AI-Enabled Smart Grids
Increasing the connectivity leads to an increase in the cyberattack surface. Different types of attacks are false-data injection, denial-of-service attacks, malicious software intrusion, compromised smart meters, malicious distributed energy resource (DER) controllers, spoofing, command and control, model poisoning, adversarial machine learning, and privacy attacks. Cyber-security is exceptionally important because cyber incidents can have physical consequences.
An example of such a cyberattack could be the case when an attacker manipulates the voltage measurements
V_reported = V_actual + Delta V_attack
An intelligent controller that is designed to rely on measurements it receives may issue an inappropriate reactive-power order. As a result, security must be achieved at many levels.
A design that uses multiple layers of security is more likely to be safe and effective. Device Level: identity assurance, authentication, and trusted firmware; Communication Level: encryption, secure routing, access control, and segmentation; Data Level: integrity checks, timestamps, and detection of irregularities; AI Level: adversarial testing, monitoring, explanation, and secure updates; Control Level: physical safety limits and override controls.
Cybersecurity research on high-DER systems is also beginning to recognize the need to make smart-grid security controls more adaptable as the number of distributed resources grows.

Results of the Cross-Layer Analysis
No Single Communication Technology Can Support the Entire Smart Grid
Smart-grid communication has extremely different requirements. Smart meters focus on coverage and cost while protection systems focus on deterministic latency and reliability. As such, heterogeneous hybrid networking is more realistic than a single-technology communication model.
Edge Intelligence Is Essential for Time-Critical Functions
Uploading any data to the distant cloud may introduce a number of network-dependent issues and, therefore, vital functions should be prioritized according to the following hierarchy: device-level security, edge intelligence, regional intelligence, and cloud analytics. In other words, the more urgent and safety-critical the process is, the closer to the physical device it should be implemented.
Communication State Should Become an AI Input
Current artificial intelligence (AI) energy frameworks typically focus on electrical and market data. The present study introduces communication variables into decision-making algorithms to enable communication-aware grid intelligence. A controller that knows that a communication link is saturated or unreliable can make different control decisions based on that knowledge.
Grid Requirements Should Influence Communication Resource Allocation
The other direction should also be integrated. Instead of all packets being treated equally by the communication network, the grid conditions should dictate the communication priorities. Messages that are related to relays or protections should have higher priority during a fault condition, followed by operational measurements and the meter data can be suspended temporarily if needed. In this way grid-aware communication networking is realized.
AI Autonomy Requires Physical Safety Constraints
Unconstrained black-box control is unsafe for critical infrastructure. AI-actuated actions must be constrained by voltage limits, thermal limits, frequency, protection coordination, stability, and equipment ratings. The future intelligent grid must therefore be a hybrid of machine intelligence and physics-based constraints and protection logic.

16. Comparison of Conventional and AI-Enabled Smart Grids

Feature	Conventional Grid	Digitized Smart Grid	Proposed AI-Enabled Grid
Power flow	Mainly one-way	Increasingly bidirectional	Fully coordinated multidirectional
Monitoring	Limited	Real-time sensing	Predictive monitoring
Decision-making	Operator/rule based	Automated rules	AI-assisted adaptive control
Communication	Limited	Two-way	Adaptive cross-layer communication

Maintenance	Scheduled/reactive	Condition-based	Predictive
Renewable integration	Limited	Supported	AI optimized
EV role	Load	Controlled load	Flexible load/storage resource
Computing	Centralized	Cloud/control centre	Device-edge-cloud
Cybersecurity	IT/perimeter oriented	Integrated	AI + cyber-physical security
Data privacy	Limited issue	Important	Federated/privacy-aware intelligence
Fault management	Detect and isolate	Automated restoration	Predictive/self-healing assistance
Network awareness	Minimal	Communication support	Communication-aware control

Discussion

The analysis that follows reveals that the next step in smarter grids is not about adding more layers of AI algorithms, but rather about integration.

Electricians typically optimize voltages, frequencies, flows, losses, and stability, while communication engineers think about throughput, latency, packet loss, and network availability. Computer scientists, in turn, are often concerned with prediction error, computational cost, and algorithmic performance. A smart grid, however, should optimize these areas simultaneously.

Recent reports also note that interoperability, privacy, scalability, and adversarial robustness are key issues in present smart grid designs. At the same time we see that from federated learning, digital twins, and AIoT perspectives there are solutions which we may adopt. Also it is out there that in communication engineering they realize 5G/6G, IoT, edge controllers, and AI driven networks can no longer be designed in isolation from power systems.

The put forth architecture of AI in CSGF puts in place a bidirectional communication structure. We see that power grid reports will feed into what communications have priority, that the state of the links will in turn determine how AI controls are applied to the actuators, and that out of all these actions comes a change in the power system dynamics. This creates a closed loop which at the same time makes the system connected and intelligent.

Major Implementation Challenges

Legacy Infrastructure: Utilities have assets with decades-long lifespans; complete replacement is capital-intensive. AI-based architecture should be compatible with legacy SCADA, protection, and communication infrastructure at a project's inception.

Data Quality: Missing measurements or incorrect sensor readings, synchronization mistakes, and labeling inconsistencies may undermine AI's efficacy.

Communication Coverage: The presence of remote and rural infrastructure may result in the impossibility of high-bandwidth communications. 18.4 AI Explainability. Grid operators should be able to understand why an algorithm suggests a particular switch, dispatch, or maintenance.

Model Drift: The changes in electricity consumption, the rise of renewable energy, network topologies, and customer behaviour patterns will require model retraining. 18.6 Cybersecurity. More connected systems mean more points of attack.

Regulatory Acceptance: AI-enabled critical infrastructure decisions need to be auditable and accountable. 18.8

Interoperability: Vendor-specific formats and legacy protocols are the major obstacles to system-wide intelligence.

Future Research Directions

Physics Informed Artificial Intelligence: Power flow equations and constraints of engineering are what we put into learning models which out produce real time physics based predictions. Safe Reinforcement Learning: in the training and deployment of RL controllers we must pay attention to voltage, frequency, and equipment issues. Physics Informed Artificial Intelligence: power flow equations and engineering constraints are what we must include in learning models which put out real time physics based predictions. Safe Reinforcement Learning: in training and deployment of RL controllers we should include voltage, frequency, and equipment issues. Federated Smart-Grid Intelligence: smart grid players like distribution utilities, substations, and microgrids may work together to improve shared AI models which do not require rehash of raw operation data.

6G and Semantic Communication: Communication hardware and software would be changed to prioritize the information of operational values by their meaning and urgency rather than their raw value. Digital-Twin-Based Control Validation. Before executing high-impact control functions, AI operators should be tested in a digital-twin-based real-time replica of the controlled system. Explainable AI for Operators. In the context of control rooms,

operators should be able to interrogate an explainable version of the model that provides contextual justification for its recommendations rather than a generic model score.
Multi-Agent Intelligence. Distributed energy resources, microgrids, electric vehicle aggregators, and storage can be organized as multi-agent systems to negotiate among themselves while maintaining the global power system's integrity. Autonomous Cyber-Recovery. Future systems can not only detect but also contain malicious activities by rerouting traffic, isolating nodes, and rolling back processes to clean models while continuing to offer power.

Proposed Future Experimental Validation
The framework can further be validated using standard power-system test networks, such as IEEE distribution or transmission test systems combined with communication-network simulation. A co-simulation environment could be formed by OpenDSS, MATPOWER or GridLAB-D power simulation platforms, NS-3 or OMNeT++ network simulator, Python-based ML/DL frameworks and IEC 61850-compliant information exchange for grid protocol modeling.
The framework can be evaluated in normal times, during sudden changes in renewable power output, at times of heavy EV charging, during feeder faults, increased communication delay, packet loss, false data injection, communication link failure, and in the case of cyberattack on DER controllers. We can evaluate the framework's performance via power and communication based performance indicators.

Electrical Metrics
voltage deviation; frequency deviation; power loss; renewable curtailment; energy not supplied; and restoration time.

AI Metrics
prediction accuracy; precision; recall; F1-score; false-alarm rate; and inference time.

Communication Metrics
End-to-end latency; packet delivery ratio; throughput; jitter; and network availability.
This combined assessment would provide a more accurate representation of actual smart-grid performance than simply testing the AI model independently.

Conclusion

The modern electrical grid is rapidly shifting toward a complex cyber-physical system, in which the electricity, information, and decision intelligence are interacting in concert. Renewable-energy resources, battery storage, plug-in hybrid electric vehicles, smart meters, autonomous and automated substations, and responsive loads are combining to create operational complexity greater than that which can be effectively managed by conventional centralized and rule-based approaches.
This research work studied the combined role of the electrical power systems, artificial intelligence (AI), computing and wireless communication technologies, and proposed the AI-enabled cross-layer smart grid framework (AI-CSGF). The framework encompasses physical power infrastructure, sensors, heterogeneous communication networks, edge intelligence, cloud intelligence, and control applications in a unified feedback structure.
The main conclusion is that future smart grids require cross-layer optimization. Artificial intelligence needs to be aware of network latencies, reliability and cybersecurity, while communication infrastructure should be cognizant of the criticality of power-system messages. Time-critical functions should employ more local edge intelligence, while intensive computations can be offloaded to regional or cloud layers. Federated learning can enable decentralized AI, while digital twins facilitate testing and assurance, and standards, such as IEC 61850, permit standardized information exchange, among other emerging enablers.
Yet increased autonomy also presents a number of potential issues. Control by AI should be limited by physical system constraints, cybersecurity, communication reliability, and human governance. The smart grid of the future will most probably not be controlled solely by AI or the communication infrastructure. Instead, it will probably rely on integrated solutions, where power engineering, computer intelligence, and communication technologies collaborate to assure safe, reliable, and cost-effective electricity in the future.

References

1. U.S. Department of Energy. Grid Modernization and the Smart Grid. Office of Electricity. https://www.energy.gov/oe/grid-modernization-and-smart-grid
2. National Institute of Standards and Technology. NIST Framework and Roadmap for Smart Grid Interoperability Standards. NIST Smart Grid Program. https://www.nist.gov/ctl/smart-connected-systems-division/smart-grid-group/smart-grid-framework

3. Gopstein, A. (2021). An Introduction to the NIST Smart Grid Interoperability Framework. EE T&D Magazine, 24(2).
4. International Electrotechnical Commission. (2026). IEC TR 61850-1-1:2026: Communication Networks and Systems for Power Utility Automation - Part 1-1: Introduction and Overview.
5. International Electrotechnical Commission. (2022). IEC 61850-5:2013+AMD1:2022: Communication Networks and Systems for Power Utility Automation - Communication Requirements for Functions and Device Models.
6. International Electrotechnical Commission. (2020). IEC TR 61850-90-12:2020: Wide Area Network Engineering Guidelines.
7. International Telecommunication Union. (2023). Recommendation Y.3122: Quality of Service Assurance Requirements and Framework for Smart Grid Supported by IMT-2020 and Beyond.
8. International Telecommunication Union. (2025). Supplement G.86: Fibre to the Power Grid Use Cases and Network Requirements.
9. Alam, M. M., Hossain, M. J., Habib, M. A., Arafat, M. Y., & Hannan, M. A. (2025). Artificial intelligence integrated grid systems: Technologies, potential frameworks, challenges, and research directions. Renewable and Sustainable Energy Reviews, 211, 115251. https://doi.org/10.1016/j.rser.2024.115251
10. Alshamasi, R. Z., & Ibrahim, D. M. (2025). Federated intelligence for smart grids: A comprehensive review of security and privacy strategies. Journal of Electrical Systems and Information Technology, 12, 43. https://doi.org/10.1186/s43067-025-00235-8
11. Zhang, Z., Rath, S., Xu, J., & Xiao, T. (2024). Federated Learning for Smart Grid: A Survey on Applications and Potential Vulnerabilities. arXiv preprint arXiv:2409.10764.
12. Galceran-Arellano, S. et al. (2024). Advancing power system services with privacy-preserving federated learning techniques: A review. IEEE Access, 12, 76753-76780. https://doi.org/10.1109/ACCESS.2024.3407121
13. Nguyen, A. T., & Ahn, Y. (2025). Edge AI for smart energy systems: A comprehensive review. IntechOpen. https://doi.org/10.5772/intechopen.1011425
14. National Institute of Standards and Technology. (2021). Distributed Energy Resource Security: Potential Guidelines and Research Topics. NIST Technical Note 2182.