Energy Reports 14 (2025) 2170–2190

Contents lists available at ScienceDirect

Energy Reports

journal homepage: www.elsevier.com/locate/egyr

Review article

Data-driven management for cyber-physical-social distribution networks: A comprehensive review and complex system-of-systems data analytics framework

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ARTICLE INFO

Keywords:
Big data
Communications
Cyber-physical distribution networks
Data analytics
Data-driven management
Distributed computing
Smart grid
Standards

ABSTRACT

The electricity industry is facing escalating energy demands, heightened market competition, and pressing environmental concerns, including air pollution and its reliance on fossil fuels. The advent of the smart grid, a next-generation power system enabling bidirectional flows of electricity and data, presents a transformative solution to these challenges. This evolution is underpinned by advancements in equipment, including sensors, smart meters, and Phasor Measurement Units (PMUs). However, integrating smart homes, Electric Vehicles (EVs), and smart cities into this infrastructure introduces unprecedented complexities that the traditional grid cannot effectively address. The smart grid relies on sophisticated data acquisition and processing systems, including Advanced Metering Infrastructure (AMI) and Intelligent Electronic Devices (IEDs), to achieve enhanced visibility and control. Data analytics frameworks must efficiently manage diverse data types and purposes, utilizing secure telecommunication networks and robust cybersecurity protocols. A critical challenge is minimizing data volume during preprocessing to mitigate cyberattack risks while ensuring system reliability. This balance between robust data-driven management and system stability is pivotal for efficiently operating cyber-physical Distribution Networks (DNs) in a complex system-of-systems architecture. This review explicitly highlights the joint role of Artificial Intelligence and Machine Learning (AI/ML) in conjunction with cybersecurity, enabling the secure and data-driven operation of cyber-physical-social DNs. We synthesize AI/ML methods for DN analytics and map the cybersecurity requirements, threats, and standards that must be co-designed with the data architecture.

1. Introduction

Communication networks provide operators with the necessary situational awareness to manage the network, coordinate with crews and other operators to maintain safety during normal operations, and efficiently manage recovery during an outage (Ogle, 2023; Mostafa et al., 2022; Kuzlu et al., 2014; Hou et al., 2016; Mouftah et al., 2019).

Scattered renewable generation sources are increasing, and people may own many; for example, smart homes can practically be both consumers, storage, and producers, and they change from producer to consumer very quickly (Rashtbaryan et al., 2024; Gharehpetian et al., 2021; Nikolovski et al., 2018; Seddigh et al., 2024). Moreover, vice versa, so it increases the complexity of the network; another problem that occurs with the increase of renewable producers is the system with low inertia, which, unlike traditional networks (Ogle, 2023; Rashtbaryan et al., 2024; Karrari et al., 2020; Ghiasi et al., 2023a; Dehghani et al., 2022), changes the operating mode of smart homes in different ways, for example, connecting or disconnecting an electric vehicle can add to this problem, thus increasing the need for data exchange to coordinate interconnected systems in smart grids, as having richer and simultaneous real-time data to process, leading to decision-making/support (Nkoro et al., 2024; Saner et al., 2022; Afshari et al., 2020a; Deilami et al., 2011). It becomes very complicated under certain conditions (Kamwa and Johnson, 2023). This infrastructure consists of a wide variety of wired and wireless technologies spread across regions, and on top of this infrastructure are several layers of communication protocols that manage how data flows (Manoharan et al., 2020; Moerman et al., 2022; Wang et al., 2023a; Almasabi et al., 2024). Throughout this paper, our cyber-physical scope is the MV/LV

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https://doi.org/10.1016/j.egyr.2025.08.049
Received 12 June 2025; Received in revised form 21 August 2025; Accepted 31 August 2025
Available online 5 September 2025

Nomenclature

PMU	Phasor Measurement Unit
AMI	Advanced Metering Infrastructure
IED	Intelligent Electronic Device
DN	Distribution Network
TOU	Time-of-Use
RTP	Real-Time Pricing
CPP	Critical Peak Pricing
DR	Demand Response
VR	Voltage Regulator
CBC	Capacitor Bank Controller
HDFS	Hadoop Distributed File System
RTU	Remote Terminal Unit
AI	Artificial Intelligence
DAP	Data Aggregation Point
WAN	Wide Area Network
BAN	Building Area Network
FAN	Field Area Network
GAN	Generative Adversarial Network
HAN	Home Area Network
IAN	Industrial Area Network
LAN	Local Area Network
MAN	Metropolitan Area Network
NAN	Neighborhood Area Network
DOCSIS	Data Over Cable Service Interface Specification
FP Growth	Frequent Pattern Growth
INSF	Iran National Science Foundation
Wi-Fi	Wireless Fidelity
WIMAX	Worldwide Interoperability for Microwave Access
FDIR	Fault Detection, Isolation, and Restoration
CPS	Cyber-Physical System
RNN	Recurrent Neural Network
PCA	Principal Component Analysis
SOM	Self-Organizing Map
AUC	Area Under the Curve
RMSE	Root Mean Square Error
RBAC	Role-Based Access Control
PHY	Physical
IPS	Internet Protocol Service
ETL	Extract Transform Load
MG	Microgrid
PIML	Physics-Informed Machine Learning
IT	Information Technology
ODW	Operational Data Warehouse
DMS	Distribution Management System
DAC	Distribution Automation Controller
PHEV	Plug-in Hybrid Electric Vehicle
PON	Passive Optical Network
PLC	Power Line Communication
LTE	Long-Term Evolution
RF Mesh	Radio-Frequency Mesh
ML	Machine Learning
DSL	Digital Subscriber Line
MPLS	Multi-Protocol Label Switching
WAMS	Wide Area Monitoring System
WDM	Wavelength Division Multiplexing
SONET	Synchronous Optical Networking
SDH	Synchronous Digital Hierarchy
ADSL	Asymmetric Digital Subscriber Line
HDSL	High-bit-rate Digital Subscriber Line
SaaS	Software as a Service
PaaS	Platform as a Service
IaaS	Infrastructure as a Service
DHS	Department of Homeland Security
ECD	Edge Computing Device
CISA	Cybersecurity and Infrastructure Security Agency
VDSL	Very high-speed Digital Subscriber Line
DSDR	Distribution System Demand Response
ORM	Outage and Restoration Management
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
SCADA	Supervisory Control and Data Acquisition
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory
EV	Electric Vehicle
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
MV/LV	Medium/Low Voltage
IDS	Intrusion Detection System
OPF	Optimal Power Flow
MAC	Media Access Control
SOC	Security Operation Center
DERMS	Distributed Energy Resource Management System
SoC	Security Operation Center
RBAC	Rule-based Access Control

Distribution Network (DN) and Microgrids (MGs), from Advanced Metering Infrastructure (AMI) enabled sensing and DN communications Home/Neighborhood/Field/Wide Area Network (HAN/NAN/FAN/-WAN) through big-data platforms (e.g., Hadoop Distributed File System (HDFS)/MapReduce) to Artificial Intelligence (AI)/Machine Learning (ML) analytics and Distribution Management System (DMS) level control, together with the associated cybersecurity requirements.

This paper proposes a comprehensive framework for managing data in cyber-physical DNs, focusing on integrating renewable energy sources, smart homes, and EVs into the grid. We address the challenges posed by the increasing complexity of network operations and the need for real-time data exchange to ensure effective coordination and decision-making. Our approach leverages advanced data analytics techniques to enhance system stability, security, and efficiency in smart grids, offering solutions for managing the complexities introduced by decentralized energy production and dynamic consumer roles. Within this scope, we (i) survey AI/ML techniques across sensing, state estimation, forecasting, control, and Demand Response (DR), and (ii) consolidate cybersecurity requirements and recent governance frameworks for critical infrastructure (e.g., Department of Homeland Security (DHS) ‘Roles and Responsibilities Framework for AI in Critical Infrastructure,’ Nov. 2024, and Cybersecurity and Infrastructure Security Agency’s (CISA’s) AI Roadmap) that must be co-designed with the data architecture.

2. Sources of smart grid data

This data includes both electrical information, such as meter data and distribution buses, and non-electrical information that cannot be measured with sensors but still affects the performance of the power system, including weather data and geographical location. Most of these data are related to smart meters and sensors that send real-time and historical information about the system status, shown in Table 1 (Zhu et al., 2018).

2.1. Meter reading

Smart meters enable two-way data exchange for billing and real-time

Table 1
Source of data in smart grids.

Applications			
(Wang et al., 2015, 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024)	Meter Reading	(Al-Ali et al., 2017; Yaghmaee Moghaddam and Leon-Garcia, 2018; Han and Lim, 2010; Hannan et al., 2018)	Outage and Restoration Management (ORM)
(Kuzlu et al., 2014; Zolin and Ryzhkova, 2021)	Load Monitoring	(Zhu et al., 2018; Wang et al., 2015)	Distribution of Customer Storage
(Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Yousefpour et al., 2018; Buyya and Srirama, 2019a; Liang et al., 2018)	Electric-Service Prepayment	(Mouftah et al., 2019; Liu, 2018; Zhu et al., 2019)	Electric Transportation
(Kuzlu et al., 2014; Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	Demand Response	(Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	Firmware Updates
(Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	Service Switch Operation	(Zhu et al., 2018; Wang et al., 2019; Mitra et al., 2024)	Customer Information and Messaging
(Zhao et al., 2014; Liu et al., 2015; Stoupis et al., 2023)	Distribution Automation	(Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	Premises Network Administration
(Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	Geographical Information	(Kuzlu et al., 2014; Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	Power Quality
(Kuzlu et al., 2014; Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	Load Control	(Wang et al., 2015; Zhao et al., 2014; Liu et al., 2015; Jamali et al., 2023)	Distribution Management
(Shahinzadeh et al., 2019; Baimel et al., 2016)	Dispatching Automation	(Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	Running State of Equipment
(Liu et al., 2015; Khodayar and	Equipment Parameters	(Wang et al., 2019; Alahakoon and Yu,	Regional Economy

Table 1 (*continued*)

Applications			
Wang, 2021; Gungor et al., 2013)		2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	
(Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	Meteorological Information	(Kuzlu et al., 2014; Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Liang et al., 2018; Buyya and Srirama, 2019a)	Pricing
(Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	Marketing System		

consumption monitoring, empowering subscribers to manage their energy usage effectively (Mlakić et al., 2019; Emadaleslami et al., 2023; Uddin et al., 2023). Meter reading varies based on distance, type of data collected, and transmission frequency. The data volume depends on the purpose and type of user (Wang et al., 2019):

- Subscriber Requests or Information Loss: Data is retrieved when subscriber details are unavailable or upon specific consumption inquiries.
- Residential and Commercial/Industrial Consumers: Consumption data is collected by smart meters for residential users 4–6 times a day at intervals of 15 min to 1 h. For commercial or industrial users, it is collected 12–24 times a day at the same intervals. The time interval for data transmission to the AMI head end is less than 4 h for residential meters and less than 2 h for commercial/industrial meters.
- Data Management Systems: The volume of collected data depends on the number of meters managed through intelligent data-receiving devices and meter data management systems.

To avoid ambiguity, we distinguish three notions: (i) the sampling interval at the meter (how often the meter records consumption), (ii) the reporting/transmission interval from the meter (or Data Aggregation Points (DAP)) to the AMI head-end, and (iii) the application/network latency (end-to-end delay for a single message or event). In typical AMI deployments, residential meters are sampled 4–6 times per day at 15-min to 1-h intervals, whereas commercial/industrial meters are sampled 12–24 times per day over the same sampling range; the reporting/transmission interval to the AMI head-end is < 4 h and < 2 h for residential and commercial/industrial meters, respectively. On-demand reads occur as needed between 07:00 and 22:00, and bulk transfers from the AMI head-end to the utility are performed daily (06:00–18:00) with a < 1 h transmission interval. Application-level latencies for customer–utility messaging are typically < 15 s. See Table 2 for a consolidated view of data types, sampling requirements, transmission intervals, and latencies."

2.2. Pricing application

Pricing applications involve transmitting price signals to smart devices, such as meters. These signals are based on various pricing tariffs, allowing users to adjust their consumption and optimize grid performance. Key pricing programs include:

Table 2
Type, accuracy, sampling rate, transmission (reporting) interval, and latency of data exchange.

Ref	Application	Data size (bytes)	Data sampling Requirement	Latency
(Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Siryani et al., 2017)	-Meter reading on demand (between meters and utility)	100	Whenever needed, from 7 am to 10 pm	<15 s
(Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Siryani et al., 2017)	-Meter reading_Scheduled interval (AMI head end and meter)	1600–2400	4–6 times per residential meter per day 12–24 times per commercial/ industrial meter per day	<4 h <2 h
(Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Siryani et al., 2017)	– Meter reading_Bulk transfer (Receiving bulk data by utility from AMI head end)	MB-scale ($\geq 10^6$ bytes; utility-specific)	As scheduled for a group of meters (typically multiple times per day; 6 am–6 pm)	<1 h
(Kuzlu et al., 2014; Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	-Real-time Pricing (Between meters and utility)	100	1 per device per price data broadcast event 4 per year	<1 min
(Kuzlu et al., 2014; Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	-Time of Use Pricing (Between meters and utility)	100	1 per device per price data broadcast event 6 per day	<1 min
(Kuzlu et al., 2014; Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	-Critical Peak Pricing (Between meters and utility)	100	1 per device price data broadcast event 2 per year	<1 min
(Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Yousefpour et al., 2018; Buyya and Srirama, 2019a; Liang et al., 2018)	-Electric service prepayment (Between customers and utility)	50–150	25 times per prepay meter per month (7 am–10 pm)	<30 s
(Kuzlu et al., 2014; Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	-DR (Between customer side Devices and utility)	100	1 per device per broadcast request event	<1 min
(Kuzlu et al., 2014; Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	-Service Switch operation (Between meters and utility)	25	1–2 per 1000 electric meters per day (8 am–8 pm)	< 1 min
(Zhao et al., 2014; Liu et al., 2015; Stoupis et al., 2023)	-Distribution automation system monitoring and maintenance (data from field devices to DMS)	100–1000	CBC: 1 per device per hour Feeder fault detector: 1 per device per week Recloser: 1 per device per 12 h Switch: 1 per device per 12 h VR: 1 per device per hour	< 5 s
(Zhao et al., 2014; Liu et al., 2015; Stoupis et al., 2023)	-Distribution automation – Volt/VAR control (Field devices receive commands from DMS)	150–250	Open/close CBC: 1 per device per 12 h Open/close switch: 1 per device per week Step up/down VR: 1 per device per 2 h	< 5 s
(Zhao et al., 2014; Liu et al., 2015; Stoupis et al., 2023)	-Distribution automation – FDIR (command from DMS to field devices)	25	1 per device per isolation/ reconfiguration event (<5 s, within <1.5 min of fault event)	< 5 s
(Al-Ali et al., 2017; Yaghmaee Moghaddam and Leon-Garcia, 2018; Han and Lim, 2010; Hannan et al., 2018)	-ORM	25	1 per meter per power lost/power returned	< 20 s
(Zhu et al., 2018; Wang et al., 2015, 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	-Distribution of customer Storage (charge/discharge command from DAC to the storage)	25	2–6 per dispatch per day	< 5 s
(Mouftah et al., 2019; Liu, 2018; Zhu et al., 2019)	-Electric transportation (PHEV receives price information from the utility side)	255	1 per PHEV per 2–4 day (7 am–10 pm)	< 15 s
(Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	-Firmware updates (Between devices and utility)	400–2000k	1 per device per broadcast event (24 ×7)	< 2 min,7days
(Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	-Updating the configuration of programs (Between devices and utilities)	25–50k	1 per device per broadcast event (24 ×7)	< 5 min,3days
(Zhu et al., 2018; Wang et al., 2019; Alahakoon and Yu, 2016; Benzi et al., 2011; Mitra et al., 2024; Buyya and Srirama, 2019a; Liang et al., 2018)	-Customer information (Utility responds to the consumers' requests for account information)	50–200	As needed (7 am–10 pm)	< 15 s
(Budka et al., 2010; Rahman et al., 2016; Kibria et al., 2018; Kuzlu and Pipattanasomporn, 2013)	-Local network management (Between customer-side devices and utility)	25	As needed (24 ×7)	< 20 s

- DAC: Distribution Automation Controller
- PHEV: Plug-in Hybrid Electric Vehicle
- Note a: Bulk-transfer payloads depend on the number of meters and compression settings; therefore, the typical order of magnitude is MB-scale and utility-specific. For comparability, sizes are reported as bytes ($\geq 10^6$).

- **Time-of-Use (TOU):** This tariff reflects the variation in the cost of supplying electricity over different periods (such as peak, mid-peak, and off-peak periods during the day or season). It is essentially a tiered rate structure that does not consider daily price fluctuations. Prices are typically higher during peak periods than off-peak periods. The purpose of this structure is to encourage customers to change their consumption behavior to use less power during peak demand periods (Paterakis et al., 2017; Yong et al., 2023).
- **Real-Time Pricing (RTP):** As demand fluctuates throughout the day, the output of different power plants with varying cost structures changes, leading to fluctuations in the final cost of generation. For this reason, energy prices are updated at very short intervals, usually

every hour. Customers are exposed to changes in local or wholesale electricity market prices through this tariff (Yong et al., 2023). This requires high-rate data collection and efficient processing, which comes with higher costs than other tariffs (Falope et al., 2024).

- **Critical Peak Pricing (CPP):** A tariff model in which the price of electricity is set significantly higher than the normal TOU rate during specific and critical periods (a few hours or days per year). These periods usually occur for particular reasons, such as extreme temperature increases, equipment failures, or the Unavailability of reserves, or power system emergencies, which can lead to unexpected changes in demand, etc (Paterakis et al., 2017). The purpose of this tariff is to reduce electricity consumption during peak demand hours and improve the reliability of the power system. In other words, the CPP tariff is the same as the TOU tariff, except that it is offered at a higher rate for a limited number of (critical) hours per year (Yong et al., 2023).

2.3. Electric service prepayment

Subscribers can prepay for utilities, including electricity, water, and gas. When their credit falls below a predefined threshold, a warning is issued. If the credit is not replenished, the service is eventually disconnected. With the advent of smart meters, this process can now be managed remotely, eliminating the need for manual credit purchases. Alerts and service disconnection commands can be sent digitally, streamlining the prepayment process.

2.4. Demand response

DR programs connect smart devices at consumption points to manage load reductions during peak periods. These programs actively regulate energy usage by sending commands to turn consumer devices on or off. Real-time pricing mechanisms are often integrated, allowing consumers to adjust their usage based on current energy costs (Liang et al., 2018).

2.5. Service switch operation

Utility services such as electricity, gas, and water can be remotely activated or deactivated by utilities or customers. This capability reduces operational costs and service time by eliminating the need for physical service trucks to access meters. Service switch operation commands, including service activation and deactivation, are executed digitally, streamlining the process (Kuzlu et al., 2014).

2.6. Distribution automation

Distribution automation provides real-time monitoring, automation control, data communication, and information management for the distribution grid. These systems enable utilities to optimize asset utilization by controlling distribution-level devices such as Capacitor Bank Controllers (CBCs), fault detectors, switches, and Voltage Regulators (VRs). Key applications include monitoring and maintaining the distribution system, voltage control, DR at the Distribution Level (DSDR), and Fault Detection, Isolation, and Restoration (FDIR) (Mouftah et al., 2019).

- Distribution System Monitoring and Maintenance: This involves self-diagnostic capabilities for equipment, scheduled polling of equipment status (e.g., open/closed, active/inactive), and retrieving sensor data to assess equipment conditions.
- Volt/VAR Control: It is designed to reduce energy losses, regulate voltage along distribution circuits, and compensate for load power factors; this application improves grid efficiency and reliability.
- DSDR Applications: Focused on reducing grid voltage during peak periods to manage system load. Automating control of capacitor banks, feeder switches, and VRs achieves this.
- FDIR Applications: Address fault detection, isolation, and restoration within the grid. These applications aim to minimize service interruptions by identifying and isolating faults, restoring service quickly, and ensuring minimal customer disruption.

2.7. Outage and restoration management

ORM systems enable utilities to detect power outages through devices like smart meters and outage detection units. These devices can report over-voltage and under-voltage situations, enhancing grid reliability. Integrating an interface module into smart meters activates the outage detection function, allowing immediate alerts when power loss occurs. To prevent false alarms, utilities typically deploy multiple outage detection units across each branch of the DN (Mouftah et al., 2019).

2.8. Distribution of customer storage

Distribution of customer storage offers a technological solution to operational challenges by providing power, energy, and rapid response capabilities within a DN. It facilitates the efficient integration of renewable energy sources by mitigating intermittency issues. Applications include deploying storage devices along distribution feeder circuits or laterals for peak load shaving, voltage support, power quality enhancement, demand control, and interruption protection (Nikolovski et al., 2018; Nimalsiri et al., 2022). These storage systems contribute to grid stability and resilience, supporting a more reliable and efficient power distribution infrastructure (Kuzlu et al., 2014; Seddigh et al., 2024).

2.9. Electric transportation

Including the flow of electricity from the vehicle side to the grid or from the grid side to the vehicle, these vehicles (hybrid, plug-in hybrid, fuel cell, plug-in fuel cell) become mobile distributed production sources (Gharehpetian et al., 2021; Buyya and Srirama, 2019a; Nimalsiri et al., 2022; Yan et al., 2023; Machlev, 2024; Fouladi et al., 2020, 2021).

2.10. Program/Configuration update

Program and configuration updates enable utilities to enhance device functionality, improve security, and meet evolving application requirements. Firmware updates address bugs or add new features to the software running on devices, while program/configuration updates adjust device settings for operational efficiency. Targeted devices include DAPs, NAN/FAN gateways, and distribution automation devices such as regulators, capacitor banks, sensors, switches, reclosers, and relays.

- Firmware Updates: Typical data size ranges from 400k to 2000k bytes, with a latency allowance of up to 7 days.
- Program/Configuration Updates: Typical data size ranges from 25 to 50 bytes, with a latency allowance of up to 3 days (Kuzlu et al., 2014).

2.11. Customer information and messaging

Customer information and messaging systems give consumers access to account details, historical electricity consumption data, and outage notifications. This information is processed through an Operational Data Warehouse (ODW) and shared via a web portal or extranet gateway linked to the utility's internal network. Utilities or third-party providers may manage these services.

- Customer Request: A typical request payload is 50 bytes.
- Utility Response: A typical response payload is 200 bytes.
- Latency Requirement: Data latency for these applications must be less than 15 s (Mouftah et al., 2019).

2.12. Premises network administration

Premises network administration allows subscribers to add or remove regional devices, such as smart meters and other smart appliances, from the network. This functionality supports the seamless integration of smart devices into the broader utility infrastructure (Alahakoon and Yu, 2016).

3. Accuracy and time frame of data exchange

Throughout this section, 'sampling' refers to the measurement rate at the source (e.g., the meter), 'transmission (reporting) interval' denotes the periodicity of forwarding data to the AMI head-end/utility back-end, and 'latency' denotes the end-to-end delay for a single transaction or event. Tables 2–3 adopt this terminology. Accurate and timely data exchange is crucial for maintaining the stability of power systems. Different data types have unique characteristics, such as sampling rates and latency requirements, based on their significance to system stability. Therefore, Tables 2 and 3 show the data types, time frame of data exchange, and data types in detail.

4. Telecommunication networks of smart grids

Communication networks are the backbone of smart grids, ensuring the correct functioning of various sub-systems. While defining a standard telecommunication architecture for intelligent networks is challenging, telecommunication technologies can be tailored to meet specific traffic demands and requirements (Sharma et al., 2022; Segatto et al., 2018). The hierarchical structure of smart grid communication networks consists of three layers, each with distinct data rates and coverage areas (Stoupis et al., 2023; Jamali et al., 2023; Biglarahmadi et al., 2022; Raeispour et al., 2020; Habibi et al., 2022a, 2021a; Afshari et al., 2020b; Dehkordi et al., 2021; Biglarahmadi et al., 2024; Wu et al., 2020; Wang et al., 2020; Jamali et al., 2022).

4.1. Local area network (LAN)

LANs operate as baseband systems, where only one signal passes through the cable simultaneously. Network nodes queue to transmit messages, sending prepared data packets sequentially. The receiver processes and reconstructs the data in the original order. LAN applications include HAN, Building Area Networks (BAN), and Industrial Area Networks (IAN), which facilitate automation and the exchange of electrical measurement data between appliances and controllers within customer premises. These networks enable (Kumar et al., 2024; Şengör et al., 2021; SaberiKamarposhti et al., 2024; Khan et al., 2023; Luo and Mahdjoubi, 2024; Han et al., 2020):

- Demand-side management
- Direct load control
- DR services for power companies

LANs connect to the smart grid through smart meters. While they do not require high bandwidth, they demand low-latency, real-time telecommunication with robust security (Habibi et al., 2022a, 2022b; Barbhaya et al., 2024; Bui et al., 2024). Their primary function is to collect essential data, such as sensor and meter readings. Due to their small geographical scope and low bandwidth requirements, LANs can operate effectively with wired or wireless technologies at the distribution level (Benzi et al., 2011; Mitra et al., 2024).

4.2. Metropolitan area networks (MANs)

The MAN layer consists of two key network types:

4.2.1. Neighborhood area networks

NANs include access points across the DN, linking smart meters and local access points. These networks form part of the AMI sub-system, facilitating communication between subscribers and the power company's control center (Mitra et al., 2024; Abdulsalam et al., 2023). Key applications include:

- Meter reading and pricing
- Prepaid electricity services
- Remote service disconnection and reconnection
- Distribution-level automation
- Electric vehicle integration

4.2.2. Field area networks

FANs provide connectivity between power distribution stations, supporting efficient coordination and control.

4.3. Wide area networks

WANs are essential in smart grids, connecting geographically dispersed sites and facilitating communication between transmission and generation sub-systems. Sometimes, WANs also support communication within distribution systems across extensive areas. They enable real-time monitoring, control, and protection of the smart grid's state. They provide communication links for the grid's backbone and cover long distances from FANs to control centers. The data transmitted over WANs is analyzed to maintain system stability under various conditions. Efficient data analysis ensures that appropriate actions are taken to preserve system stability, even when dealing with large volumes of data. This is particularly important in scenarios involving high penetration levels of renewable energy sources and distributed generation. In summary, WANs play a pivotal role in the hierarchical communication structure of smart grids, enabling seamless integration and coordination across different sub-systems to ensure reliable and efficient power delivery (Kamwa and Johnson, 2023; Zolin and Ryzhkova, 2021).

Table 3
Data types in power systems.

Data Type	Sampling Rate	Latency Requirement	Importance of Stability
PMUs	10–60 samples per second	Real-time	Provide synchronized voltage and current measurements for system monitoring and protection.
SCADA Measurements	Every 2–10 s	Seconds	Monitor system parameters like voltage, current, and frequency for operational control.
Smart Meter Data	Every 15 min to hourly	Minutes to hours	Record consumer energy usage for billing and DR; less critical for real-time stability.
Weather Data	Every few minutes	Minutes	Inform load forecasting and renewable generation predictions; impact system planning and stability.
Market Data	Varies (e.g., every 5 min)	Minutes	Influences economic dispatch and unit commitment decisions; indirectly affects system stability.

- PMU: Phasor Measurement Units
- SCADA: Supervisory Control and Data Acquisition
- Understanding these data characteristics enables effective system design and operation, ensuring timely responses to maintain grid stability.
- Note: The sampling rates and latency requirements are of typical value and may vary based on specific system configurations and operational needs.

5. Communications technologies in the smart grid

In smart grids, communication technologies are tailored to the specific requirements of different network layers: HAN, NAN, and WAN. Each layer has distinct needs concerning distance, cost, and accessibility, necessitating various telecommunication technologies (Panahazari et al., 2023; Sikri et al., 2023; Yang et al., 2023; Ghiasi et al., 2023b). As shown in Tables 4 and 5. To enhance the understanding of the hierarchical communication structure within smart grids, a multi-layer structure of an intelligent network is presented in Fig. 1. By examining Fig. 1, the readers can understand how various communication technologies are deployed across different layers to ensure efficient, reliable, and secure data exchange within the smart grid infrastructure.

To improve readability, Fig. 2 visualizes the comparative capabilities of representative communication technologies across HAN, NAN, and WAN. Panel (a) shows the typical maximum data rate, while panel (b) depicts the coverage range. The values are compiled from Table 5.

6. Data collection

In smart grid communication networks, after data is exchanged through various telecommunication technologies, a substantial volume of information is collected by diverse devices and transmitted to processing centers. Data collection is essential for monitoring, controlling, and optimizing the grid's performance. The collected data encompasses real-time power usage, system status, and other critical metrics, which are analyzed to ensure efficient energy distribution and maintain system stability (Yang et al., 2023; Singh et al., 2021; Moudoud and Cherkaoui, 2023). AMI systems play a pivotal role in this process by facilitating two-way communication between smart meters and utility providers, enabling real-time data acquisition and remote management of devices (Mitra et al., 2024; Mlakić et al., 2019; Abdulsalam et al., 2023; Xiao et al., 2023; Alsharif et al., 2024; Vodyaho et al., 2024; Hasan et al., 2024; Gaber et al., 2023; Dileep, 2020). Efficient data collection mechanisms are vital for the smart monitoring of distribution grids. Adaptive data collection strategies can enhance smart metering infrastructures' resilience, reliability, and security, ensuring that data is gathered on time to meet communication requirements and standards. To better understand the key devices involved in data collection, intelligent data collection devices are presented in Table 6, which provides an overview of the tools and technologies used in this process. These devices play a significant role in ensuring the timely and accurate aggregation of information critical to the effective operation of modern power systems. In summary, the data collection phase in smart grids involves aggregating large volumes of information from various devices across the network and transmitting it to processing units. This process is fundamental to modern power systems' effective operation and stability.

7. Data storage

Hadoop, a large volume of data, consists of two storage parts, HDFS, and one processing part (map/reduce) (Zeb et al., 2024; Olson, 2010; Zikopoulos and Eaton, 2011). It is designed to reliably store massive data sets and transfer them to user applications with high bandwidth. It divides large data into smaller blocks, distributes them among a cluster's nodes, and sends a map/reduce code packet for processing. Nodes should be processed in parallel to speed up data processing. By distributing storage and computing across many servers, the resource can grow as demand increases (Zolin and Ryzhkova, 2021; Baimel et al., 2016; Segatto et al., 2018).

8. Data analysis

In the data analysis phase, collected data is scrutinized to extract meaningful insights, with methodologies varying based on data type and scale, as outlined in Table 7. Storing data in earlier stages ensures that historical records can be utilized to reconstruct missing information if transmission sequences are incomplete. Techniques such as Generative Adversarial Networks (GANs) have been employed, improving accuracy in missing data reconstruction within smart grids (Mekala et al., 2024; Li et al., 2024a; Yilmaz and Korn, 2024; Yilmaz, 2023; Xu et al., 2025; Chen et al., 2021; Li et al., 2024b). By leveraging stored historical data and using advanced imputation methods, the integrity and continuity of data analysis are maintained, facilitating reliable decision-making processes in smart grid operations (Table 9) (Zhu et al., 2019; Reka et al., 2024).

8.1. Data mining

Data mining in smart grids involves three layers of computation: fog, cloud, and edge. Each layer plays a distinct role in efficiently managing

Table 4
Communication technologies in smart grid network layers.

Network Layer	Communication Technologies	Data Rate	Coverage Range	Application
HAN	- Wireless: ZigBee, Wi-Fi, Bluetooth, Z-Wave	- Up to 250 kbps (ZigBee)	- Within a home	- Communication Network Requirements for Major Smart Grid Applications
	- Wired: PLC, Ethernet	- Up to 100 Mbps (Ethernet)	- Within a building	
NAN	- Wireless: WiMAX, LTE, RF Mesh	- Up to 75 Mbps (WiMAX)	- Neighborhood level	- Communication Technologies in Smart Grid at Different Network Layers
	- Wired: Fiber Optic, DSL	- Up to 1 Gbps (Fiber Optic)	- Up to 5 km	
WAN	- Wireless: Microwave, Satellite	- Up to 1 Gbps (Microwave)	- Regional to national	- The Smart Grid Hierarchical Network
	- Wired: Fiber Optic, MPLS	- Up to 100 Gbps (Fiber)	- Nationwide	

- PLC: Power Line Communication
- Wi-Fi: Wireless-Fidelity
- WiMAX: Worldwide Interoperability for Microwave Access
- LTE: Long-Term Evolution
- RF Mesh: Radio-Frequency Mesh
- DSL: Digital Subscriber Line
- MPLS: Multi-Protocol Label Switching

Note: Data rates and coverage ranges are approximate and can vary based on specific technologies and deployment scenarios.
Selecting appropriate communication technologies for each network layer is crucial to ensure efficient, reliable, and secure data exchange within the smart grid infrastructure.

Table 5
Comparison of communication technology for the smart grid.

Ref	Technology	Standard/protocol	Maximum data rate	Coverage range	Networks		
					LAN	MAN	WAN
	Wire communication technologies						
(Mishra et al., 2019; Tang and Sui, 2017)	Fiber optic	PON, WDM, SONET/SDH	155 Mbps–2.5 Gbps, 40 Gbps, 10 Gbps	Up to 60 km, Up to 100 km, Up to 100 km			×
(Zhao et al., 2014; Anitha et al., 2023)	DSL	ADSL, HDSL, VDSL	1–8 Mbps, 2 Mbps, 15–100 Mbps	Up to 5 km, Up to 3.6 km, Up to 1.5 km		×	
(Sharma et al., 2022; Gungor et al., 2011)	Coaxial Cable	DOCSIS	172 Mbps	Up to 28 km		×	
(Kuzlu and Pipattanasomporn, 2013; Akpakwu et al., 2018)	PLC	Home Plug, Narrowband	14–200 Mbps, 10–500 kbps	Up to 200 m, Up to 3 km	×	, ×	
(Akpakwu et al., 2018; Al-Fuqaha et al., 2015)	Ethernet	802.3x	10 Mbps–10 Gbps	Up to 100 km	×	×	
	Wireless communication technologies						
(Sharma et al., 2022; Gungor et al., 2011)	Z-Wave	Z-wave	40 kbps	Up to 30 m	×		
(Sharma et al., 2022; Gungor et al., 2011)	Bluetooth	802.15.1	721 kbps	Up to 100 m	×		
(Han and Lim, 2010; Yao et al., 2024)	Zigbee	Zigbee, Zigbee Pro	250 kbps, 250 kbps	Up to 100 m, Up to 1600 m	×	×	
(Kibria et al., 2018; Yao et al., 2024; Zhang et al., 2019)	WIFI	802.11x	2–600 Mbps	Up to 100 m	×	×	
(Kibria et al., 2018; Zhang et al., 2019)	WIMAX	802.16	75 Mbps	Up to 50 km		×	×
(Kibria et al., 2018; Zhang et al., 2019)	Wireless Mesh	RF mesh, 802.11, 802.15, 802,16	Depending on the selected protocol	Depending on deployment	×	×	
(Sharma et al., 2022; Gungor et al., 2011)	Cellular	2 G, 2.5 G, 3 G, 3.5 G, 4 G	14.4 kbps, 144 kbps, 2 Mbps, 14 Mbps, 100 Mbps	Up to 50 km		×	×
(Sharma et al., 2022; Gungor et al., 2011)	Satellite	Satellite Internet	1 Mbps	100–6000 km			×

- PON: Passive Optical Network
- WDM: Wavelength Division Multiplexing
- SONET: Synchronous Optical Networking
- SDH: Synchronous Digital Hierarchy
- ADSL: Asymmetric Digital Subscriber Line
- HDSL: High-bit-rate Digital Subscriber Line
- VDSL: Very high-speed Digital Subscriber Line
- DOCSIS: Data Over Cable Service Interface Specification
- DSL: Digital Subscriber Line

and analyzing data.

8.1.1. Cloud computing

Cloud computing provides users with access to various processing and analytical resources over the Internet, eliminating the need for significant infrastructure or human resource investment. Built on virtualization technology, cloud computing allows multiple operating systems to run on a single physical server, improving resource utilization and efficiency (El-Sayed et al., 2018; Shaikh et al., 2023; Tang et al., 2023; Snehi and Bhandari, 2021; Wang et al., 2023b; Zhang et al., 2023a).

This service offers three primary models:

- Software as a Service (SaaS): For end users.
- Platform as a Service (PaaS): For developers and programmers.
- Infrastructure as a Service (IaaS): For network and Information Technology (IT) professionals (Mishra et al., 2019; El-Sayed et al., 2018; Mell and Grance, 2011; Armbrust et al., 2010).

8.1.2. Fog computing

Like cloud computing, Fog computing performs localized storage and data processing but is situated closer to end users. It divides tasks into multiple edge nodes, enabling more immediate control and processing capabilities (Salloum et al., 2019; Zhang et al., 2023b; Zainab et al., 2021; Naha et al., 2018). Unlike centralized data centers, fog computing determines which information can be processed locally and which should be sent to the cloud, thereby reducing the load on cloud servers and complementing cloud computing (Stoupis et al., 2023; Kuzlu and Pipattanasomporn, 2013; Akpakwu et al., 2018; Al-Fuqaha et al., 2015; Li et al., 2023; Zainab et al., 2021).

8.1.3. Edge computing

Edge computing integrates communication, data processing, and analysis functionalities, positioning itself between consumers and utility providers. Edge Computing Devices (ECDs) connect to network devices, such as sensors and switches, through wired or wireless communication (Zhang et al., 2023b; Zainab et al., 2021; Naha et al., 2018; Joglekar et al., 2021; S and Jebaseelan, 2024; Zhang, 2022; Mishra and Ray, 2023). They can also communicate with peers within the same distribution system, enhancing redundancy and resilience. Furthermore, ECDs interface with upstream systems, including cloud services and control centers, ensuring seamless integration and operational efficiency (Zhu et al., 2018; Kuzlu and Pipattanasomporn, 2013).

To provide a clearer understanding of the differences and similarities among various distributed computing paradigms, Table 8 offers a comparative analysis of Cloud, Fog, and Edge Computing.

9. Solution in case of insufficient data

In data analysis, addressing missing or anomalous values is crucial to maintaining the integrity and accuracy of results. Standard techniques include deletion, interpolation, and advanced imputation methods. For instance, the *dropna()* function in data manipulation libraries (in Pandas, Python) can remove observations or features with missing values. However, this may reduce the dataset's size and potentially introduce bias. When encountering anomalous values, it is essential to determine their validity within the application's context. Anomalies resulting from sensor errors or data processing issues can be treated as missing values or corrected using historical data (Zhu et al., 2019, 2015). Otherwise, if they represent rare but possible events, they should remain in the dataset as "black swan" occurrences. Transformations can

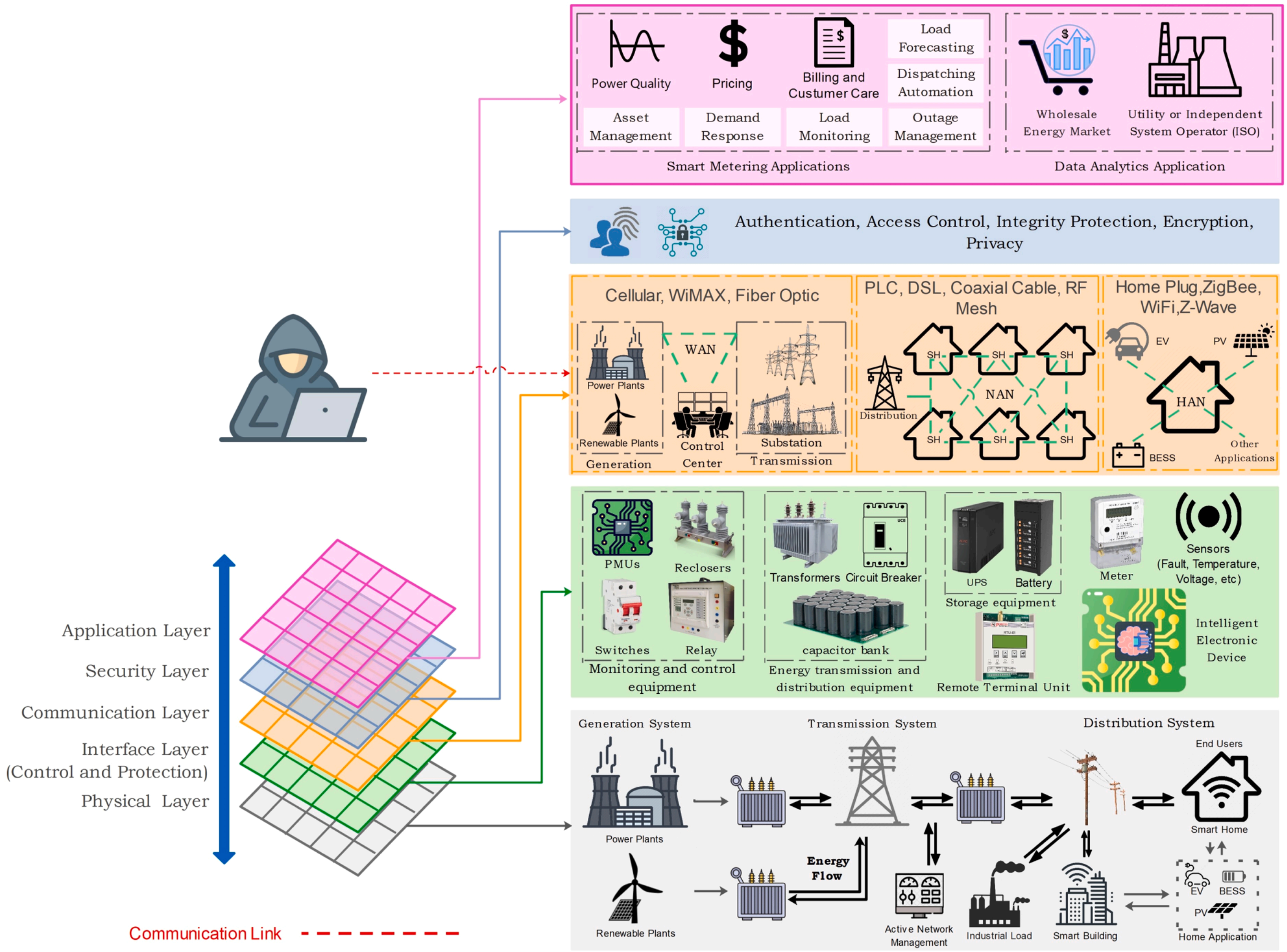

Fig. 1. The multi-layer structure of a smart network.

enhance data distribution for datasets exhibiting significant skewness (Zhu et al., 2019; Zikopoulos and Eaton, 2011; Reka et al., 2024). Applying a logarithmic transformation, for example, can make highly skewed distributions less skewed, thereby aiding in meeting the assumptions of inferential statistics and creating more interpretable patterns. By implementing these strategies, data analysts can ensure more robust and reliable outcomes in their analyses (Gungor et al., 2011). (Table 9)

9.1. Types of artificial intelligence methods

The approach of each method is described below, and an overview of this category is also presented in Fig. 3.

9.1.1. Supervised Learning

In supervised learning, each training instance comprises a feature vector (input) and a corresponding label (target output), which serve as guidance for model training. This approach enables the model to learn underlying patterns within the data and generalize its predictions to unseen test samples (Dike et al., 2018). A critical prerequisite for achieving satisfactory performance in this method is the availability of a substantial volume of accurately labeled data, the acquisition of which often demands considerable time (Lee et al., 2023).

Typical DN use-cases of supervised learning include (i) short- to medium-term load and renewable forecasting; (ii) non-intrusive load monitoring and appliance classification; (iii) fault/incipient failure classification in feeders and equipment; (iv) topology/phase identification and power-quality event classification. Representative models are linear/logistic regression, support vector regression/classification, random forest/gradient boosting, and shallow/deep neural networks (e.g., Convolutional/Recurrent Neural Network (CNN/RNN) and Long Short-Term Memory (LSTM)) when labeled AMI/PMU/SCADA data are available (Wang et al., 2019; Alahakoon and Yu, 2016; Khodayar and Wang, 2021; Chen and Ran, 2019).

9.1.2. Unsupervised Learning

Unlike the previous model, this model attempts to discover the hidden structure of data without using labeled data. In other words, in this method, algorithms receive a set of inputs without having a desired output and analyze and cluster them based on their inherent characteristics (Dike et al., 2018).

In DN analytics, unsupervised learning is used for (i) anomaly detection and cyber-attack precursors in AMI/PMU streams; (ii) clustering of customers/Distributed Energy Resources (DERs) to design DR programs and tariffs; (iii) dimensionality reduction of high-frequency PMU data; and (iv) pattern mining of switching and event logs. Standard algorithms include k-means/k-medoids, hierarchical clustering/DBSCAN, Principal Component Analysis (PCA)/Self-Organizing Map (SOM), and frequent-pattern mining (Apriori/FP-Growth) (Jamali et al., 2023; Kibria et al., 2018; Fan et al., 2018; Reka et al., 2024).

9.1.3. Semi-Supervised Learning

To address the limitation of supervised learning models, which require a large set of labeled data that can be time-consuming,

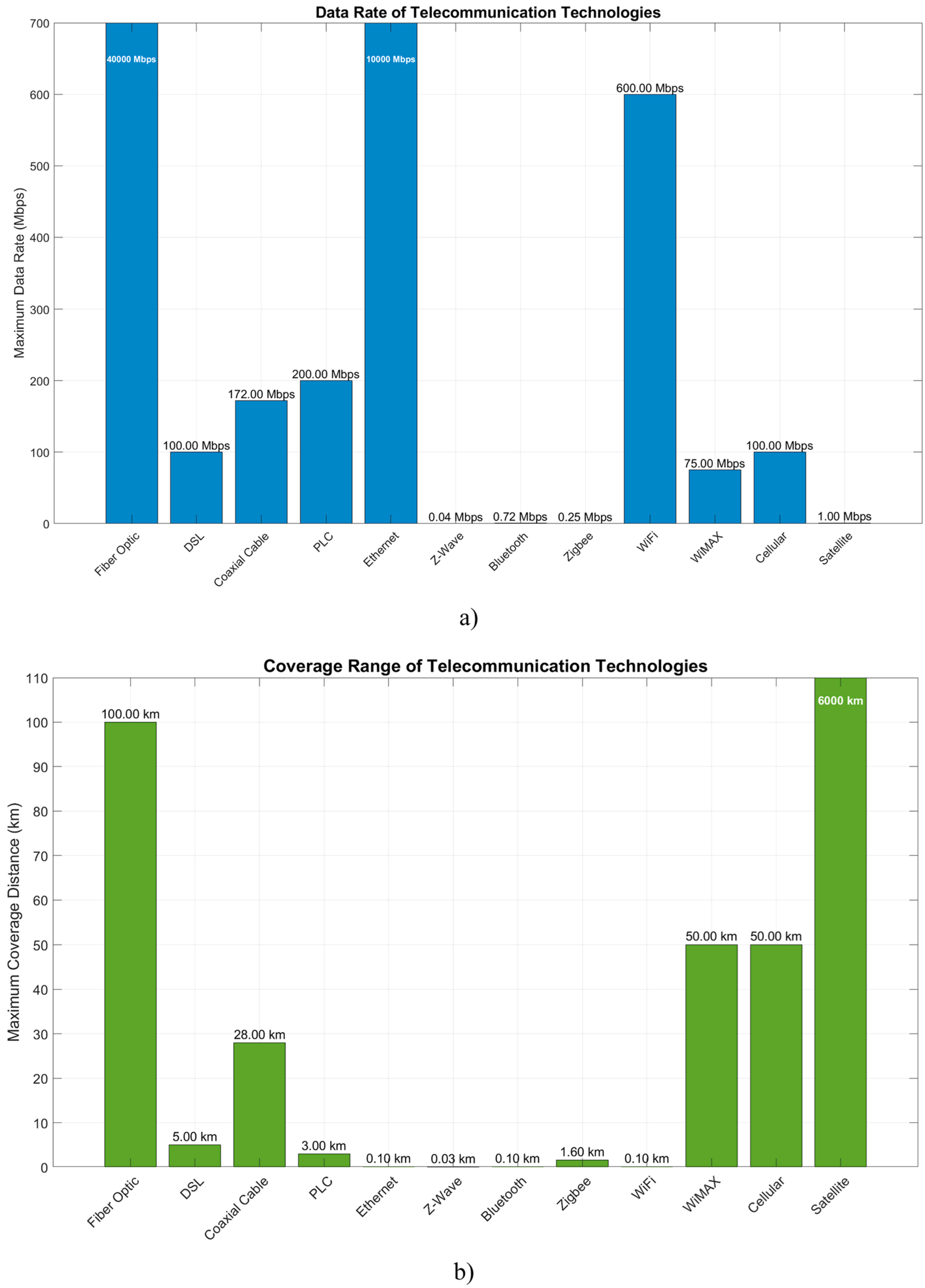

Fig. 2. Communication technologies across smart-grid layers. (a) Maximum data rate for representative wired and wireless technologies used in HAN, NAN, and WAN; (b) Typical coverage range for the same set. Data compiled from Table 5.

expensive, and difficult to obtain, this model improves performance by combining a small amount of labeled data with a large amount of unlabeled data. Assuming that the unlabeled/labeled data are drawn from the same marginal distribution, the unlabeled data will provide valuable information (Dike et al., 2018; Huang et al., 2014).

9.1.4. Reinforcement Learning

This method focuses on the interaction of the agent with the environment. Unlike supervised learning methods, this method does not require predetermined input/output data. By performing various actions and receiving rewards or feedback from the environment, the agent

Table 6
Intelligent data collection devices.

Ref	Device	Technology	Application
(Kamwa and Johnson, (2023); Zolin and Ryzhkova, (2021); "IEEE Vision for Smart Grid Controls: (2030) and Beyond, Reference Model and Roadmap Bundle),".)	WAMS	It includes a digital microprocessor for modernly dispatching PMUs remotely and in different geographical areas.	Establishing the dynamic stability of the network
(Refaat et al., 2021; Chen and Ran, 2019; El-Sayed et al., 2018)	AMI	Creating a platform for two-way data exchange between subscribers and the company. The data of smart devices on the consumption side, such as smart meters, are collected through communication networks and delivered to data management systems.	Power quality monitoring and remote meter configuration, dynamic tariffs, and local control
(Hou et al., 2016; Tang et al., 2017; Buyya and Srirama, 2019b)	PMU	A device that measures current, voltage, and frequency in real-time from 30 to 60 times per second to coordinate with other meters and uses a common time source.	Measurement of voltage, current, and frequency waveforms
(Jusoh et al., 2014; Qin et al., 2024; Li et al., 2022)	RTU	A microprocessor receives commands from the control centers, digitizes them, and executes commands in substations to monitor the status, sequence of events, binary code decimals, etc.	Collect information on system operation status.
(Zhu et al., 2018; Rahman et al., 2016; Fan et al., 2018; Yalçın et al., 2024)	SCADA	It is a specialized computer system that communicates with others through various communication protocols and processes to sense data in real-time. It monitors industrial processes such as the operation of power grid components.	Data processing and monitoring
(Tang et al., 2017; Buyya and Srirama, 2019b; Jácome-Barrionuevo et al., 2023; Baek et al., 2022)	IED	This equipment supervises and monitors scattered production, feeders, and substations, and communicates between the entities involved, such as electric vehicle charging systems and home automation, the MG area, etc.	A combination of different relay protection functions with measurement, recording, and monitoring

- RTU: Remote terminal unit
- IED: Intelligent electronic device
- WAMS: Wide area monitoring system

Table 7
Concept related to data analysis.

ref	Concept	Description
(Kibria et al., 2018; Ahmed et al., 2022; Li et al., 2023; Salloum et al., 2019)	AI	The exploration of intelligent systems and agents endowed with the capacity to learn from their environments and address complex issues
(Buyya and Srirama, 2019b; L'Heureux et al., 2017; Hossain et al., 2019)	ML	A methodological approach aimed at comprehending the underlying principles within data, as well as the extraction of pertinent information
(Khodayar and Wang, 2021; Zhang et al., 2019; Chen and Ran, 2019; Syed et al., 2021)	Deep learning	A specialized domain within ML characterized by intricate architectures of neural networks
(Zhu et al., 2018; Fan et al., 2018; Cheng et al., 2018)	Data mining	The computational analysis of data aimed at unearthing significant insights within extensive data repositories, employing knowledge from statistics, ML, and database systems
(Mostafa et al., 2022; Liu, 2018; Kibria et al., 2018)	Pattern recognition	A specific sector of ML that emphasizes the identification of patterns within data
(Mostafa et al., 2022; Wang et al., 2019; Kibria et al., 2018; Cheng et al., 2018)	Statistics	The examination of data acquisition, analytical processes, and interpretative techniques utilizing mathematical methodologies may reveal potential correlations grounded in established hypotheses.

Table 8
Comparison of distributed computing.

Characteristics	Cloud	Multi-Cloud	Fog	Edge
Latency	High	Very High	low	low
Bandwidth Utilization	High	Very High	low	Very low
Response Time	High	High	low	low
Storage	High	Very High	low	low
Server Overhead	Very High	High	low	Very low
Energy Consumption	High	High	low	low
Network Congestion	Very High	High	low	low
Scalability	Medium	Medium	High	High
Quality of Service and Quality of Experience	Medium	Medium	High	High

gradually learns a policy to maximize its cumulative rewards (Wang et al., 2024). This method is essentially a type of trial-and-error learning where the agent continuously operates in the environment, generating events, and adjusting its behavior based on the results. In other words, the results are not predetermined. The learning process involves striking a balance between exploring to discover new information and exploiting existing knowledge to make optimal decisions (Dike et al., 2018).

In Cyber-Physical System (CPS) DNs, RL has been explored for volt/VAR control, DER dispatch, and economic/secure Optimal Power Flow (OPF), MG energy management, service restoration, and EV smart charging coordination under uncertainty. In safety-critical settings, safe/model-based RL and physics-informed constraints are preferred to ensure stability, constraint satisfaction, and cyber-resilience during exploration (Nkoro et al., 2024; Wang et al., 2023a; Habibi et al., 2022a, 2021a, 2021b; Renjith et al., 2024; Hajian et al., 2024; Banaeian Far et al., 2023; Marti-Puig et al., 2024; Gutierrez-Rojas et al., 2023).

These AI method families feed into the CPS data analytics framework detailed in Section 10, where data architecture and cybersecurity are co-

Table 9
Data retrieval methods.

Category	Algorithm	Description
Supervised Learning	Decision tree	A non-parametric technique characterized by a tree-like structure wherein the terminal nodes signify class labels, and the branches embody conjunctions of features.
	Naive Bayes	A probabilistic approach grounded in Bayes' theorem, predicated on the postulation of independence among each pair of features
	Support vector Machine classifier	An algorithm designed to ascertain a separating hyperplane between the two distinct classes through the mapping of labeled data into a high-dimensional feature space
	K Nearest Neighbor	A non-parametric method that hinges upon the principle of minimum dissimilarity between novel instances and the labeled instances across various classes
	Random Forest	An algorithm that comprises a set of simplistic tree predictors functioning independently to estimate the outcome
Unsupervised Learning	K-means	An unsupervised learning methodology that operates with a predetermined number of clusters to categorize data based on the centroid, which is defined as the average value within each cluster
	K-medoids	An unsupervised learning technique akin to k-means, which designates the centroid of each cluster as an existing data point rather than employing the average value
	Hierarchical Clustering	A density-based clustering algorithm aimed at the identification of clusters characterized by specific shapes in their distribution
	DBSCAN	A density-based clustering methodology designed to discern clusters exhibiting geometric configurations within a given distribution
	Expectation Maximization	An iterative approach to estimating maximum likelihood parameters for model specifications
Correlation	FP Growth Algorithm	A proficient technique for extracting the comprehensive array of frequent patterns utilizing a specialized data structure known as the frequent-pattern tree, while preserving all associative information
	Apriori Algorithm	A traditional algorithm in data analytics aimed at uncovering latent association rules among frequently occurring items
Dimensionality reduction	Principal Component Analysis	An orthogonal transformation technique is applied to data, generating a novel coordinate system in which the principal variance is projected onto the initial coordinate axis
	Self-organizing Map	A specific form of artificial neural network developed for a low-dimensional representation of the training data space
Dimensionality reduction	Random Matrix	An algorithm that elucidates potential regulations through the utilization of high-order matrices for extensive datasets via eigenvalue decomposition

- DBSCAN: Density-Based Spatial Clustering of Applications with Noise
- FP Growth: Frequent Pattern Growth

designed with AI/ML for secure, scalable DN operations.

9.2. Reported outcomes of AI/ML studies in distribution networks

To address the heterogeneity of AI/ML applications reported across the cited literature, we consolidate in Table 10 representative studies already mentioned in this paper and summarize their key outcomes. For each analysis, we report: (i) the task and dataset used, (ii) sampling rate/window or data cadence, (iii) accuracy metrics as reported (e.g., Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), F1, Area Under the Curve (AUC)), and (iv) an indicator of computational complexity (e.g., parameter count, training/inference time, or compute footprint). Where a paper does not report an item explicitly, we mark it as 'NR'. Where appropriate, we map application-level sampling/latency constraints to our data-exchange taxonomy (Section 3, Tables 2–3) to contextualize the reported results.

Overall, we observe that PMU/IED-driven analytics operate at sub-second to tens-of-milliseconds cadences, anomaly detection and FDIR often report classification metrics (F1/AUC), while forecasting and imputation studies typically report MAE/RMSE/MAPE. Most works report task-level accuracy but under-report model complexity; we therefore provide a lightweight complexity proxy (parameters or timing) when available.

Reporting conventions: For forecasting/imputation, we list MAE/RMSE/MAPE; for detection/diagnosis, we list F1/AUC/precision–recall when available. Complexity is proxied by parameter count or reported training/inference time; when neither is provided, we mark 'NR'. Where a paper omits sampling/window, we align the task with our application-level data cadence taxonomy (Section 3, Tables 2–3).

10. A complex system-of-systems cyber-physical-social data analytics framework

Building on the empirical outcomes consolidated in Table 10, Sections 10.1–10.4 operationalize an integrated AI/ML–data-architecture–cybersecurity triad for secure DN analytics at scale.

Sections 10.1–10.4 present an integrated AI/ML–data-architecture–cybersecurity triad and a unified operational framework (see Fig. 5) to implement secure DN analytics at scale. This comprehensive analysis explored the interplay between cyber, physical, and social components within modern power systems. The structure of the cyber-physical-social power system shown in Fig. 5 illustrates the integration of physical and cyber components within smart grids, showcasing the relationship between real-time data collection, communication networks, and decision-making processes. This structure is fundamental for ensuring system stability, optimized energy distribution, and responsiveness to changing demands and potential faults within the grid. The integration of these domains necessitates a holistic framework that addresses the multifaceted challenges and opportunities arising from their convergence.

Scope of the cyber-physical study. In this review, "cyber-physical" refers to MV/LV DNs and MGs, including DERs, AMI/Smart-metering, EV integration, and DR programs; the cyber layer spanning HAN/NAN/FAN/WAN communication and utility platforms (e.g., SCADA/DMS); the data architecture from edge/fog to cloud (e.g., HDFS/MapReduce) supporting big-data analytics; AI/ML functions for sensing, state estimation, forecasting, control, fault location/restoration, and operation under limited observability; and the cybersecurity surface (threats, adversarial AI) and controls (monitoring, detection, governance). Out of scope are bulk transmission-level market design, detailed Physical (PHY)/Media Access Control (MAC) protocol engineering, and cryptographic proofs; we reference such works only insofar as they interface with DNs. (see CPS structure and Fig. 4; triad of AI–data-architecture–cybersecurity; comms layers; big-data stack; limited-observability operations; DHS/CISA governance updates).

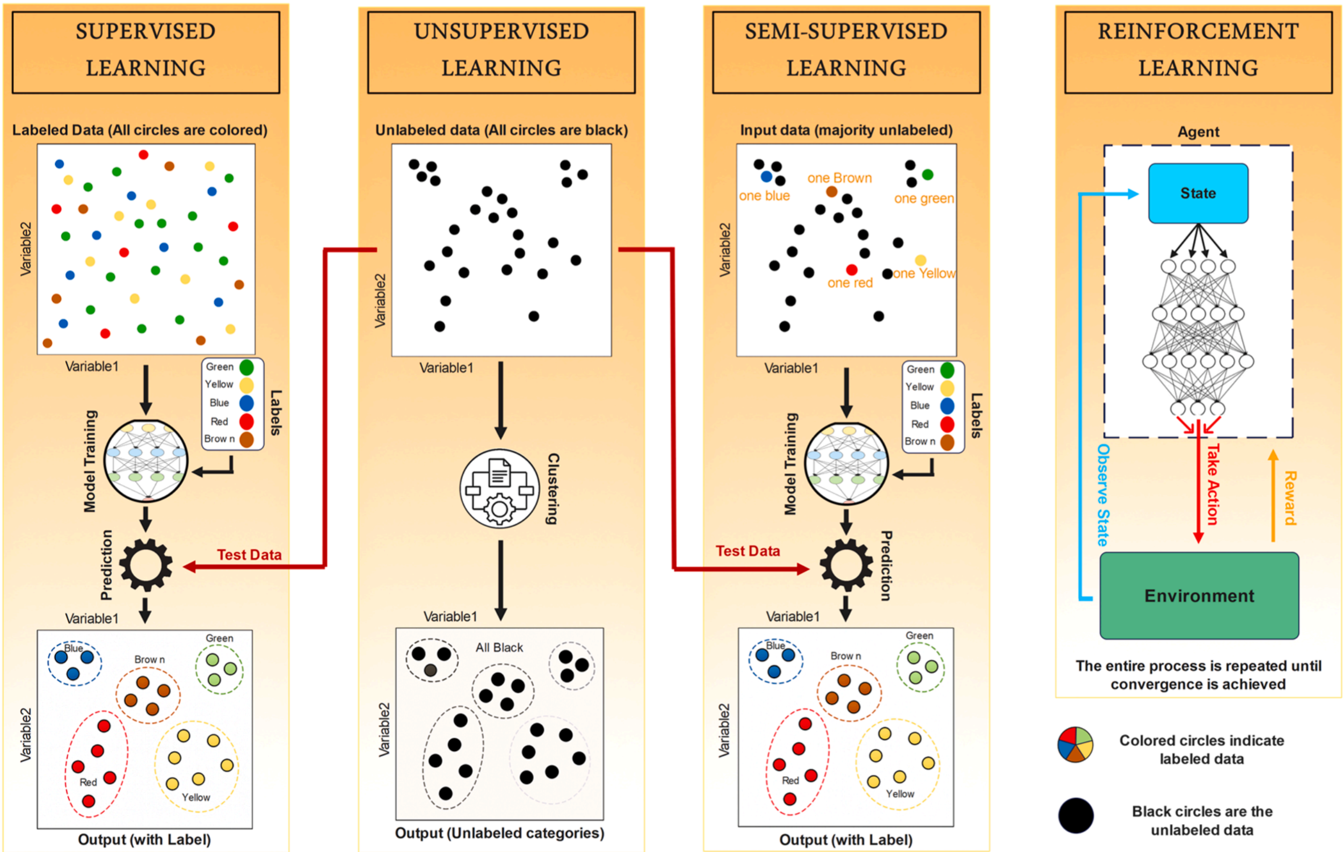

Fig. 3. Artificial Intelligence Methods.

Table 10
Outcomes of AI/ML studies already cited in this paper.

Task	Data used	Sampling/ window	Dataset size	Reported accuracy	Complexity proxy	Deployment level
Missing data imputation (GAN-based)	AMI/SCADA historical	not reported	not reported	RMSE / MAE	Params / train-infer time	Cloud / Edge
Reinforcement learning for DR/ control	Simulated DN / test bench	not reported	not reported	Reward/regret (as reported)	not reported	Edge / Fog

10.1. *Integration of artificial intelligence and machine learning*

AI and ML have improved cyber-physical-social power systems' efficiency, resilience, and adaptability. These technologies facilitate advanced data analytics, predictive maintenance, and real-time decision-making, optimizing system performance. However, deploying AI/ML models requires meticulous attention to data quality and security to prevent adversarial attacks and ensure robust operation (Nkoro et al., 2024; Wang et al., 2023a; Kibria et al., 2018; Habibi et al., 2022a, 2021a, 2022b, 2021b; Renjith et al., 2024; Hajian et al., 2024; Banaeian Far et al., 2023; Marti-Puig et al., 2024; Gutierrez-Rojas et al., 2023).

10.2. *Synthetic and adversarial data generation*

The generation of synthetic data, including adversarial examples, plays a crucial role in training AI models, especially when real-world data is scarce or poses privacy concerns. While this approach aids in model development, it introduces challenges related to data authenticity and potential vulnerabilities to adversarial attacks (Li et al., 2024a; Yilmaz and Korn, 2024; Yilmaz, 2023; Xu et al., 2025; Li et al., 2024b; Yang, 2024; Gipiškis et al., 2023; Tian et al., 2022). Physics-Informed Machine Learning (PIML) emerges as a promising solution, integrating physical laws into AI models to enhance accuracy and reduce reliance on synthetic data.

10.3. *Data architecture and cybersecurity*

Fig. 6 summarizes the unified AI/ML–data-architecture–cybersecurity triad. It shows where security controls are embedded along the data paths that feed AI/ML analytics and operational decision loops. Figs. 2 and 4 are intended to improve readability by visualizing technology trade-offs across grid communication layers and by signposting the unified AI/ML–data-architecture–cybersecurity perspective highlighted throughout this review.

Robust data architecture is fundamental to the seamless operation of cyber-physical-social systems. It ensures efficient data flow, storage, and accessibility across various system components. Concurrently, cybersecurity measures must be intricately woven into this architecture to safeguard against potential threats. The interdependence of AI, data architecture, and cybersecurity forms a triad that must be addressed collectively rather than in isolation to maintain system integrity.

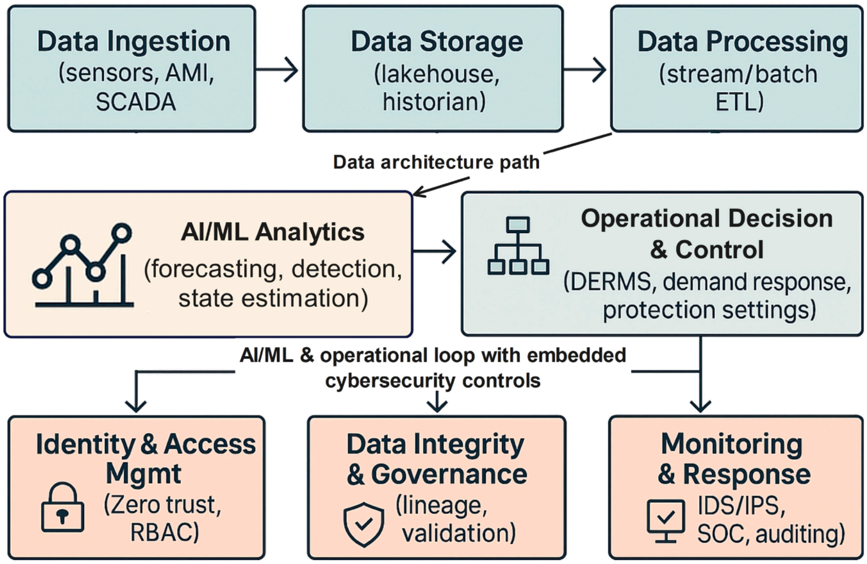

Fig. 4. Unified AI/ML–data-architecture–cybersecurity triad for CPS DNs. The figure highlights (i) data ingestion, storage, and processing layers; (ii) AI/ML analytics and control loops; and (iii) embedded cybersecurity controls (identity/access management, data integrity, monitoring) across the data paths.

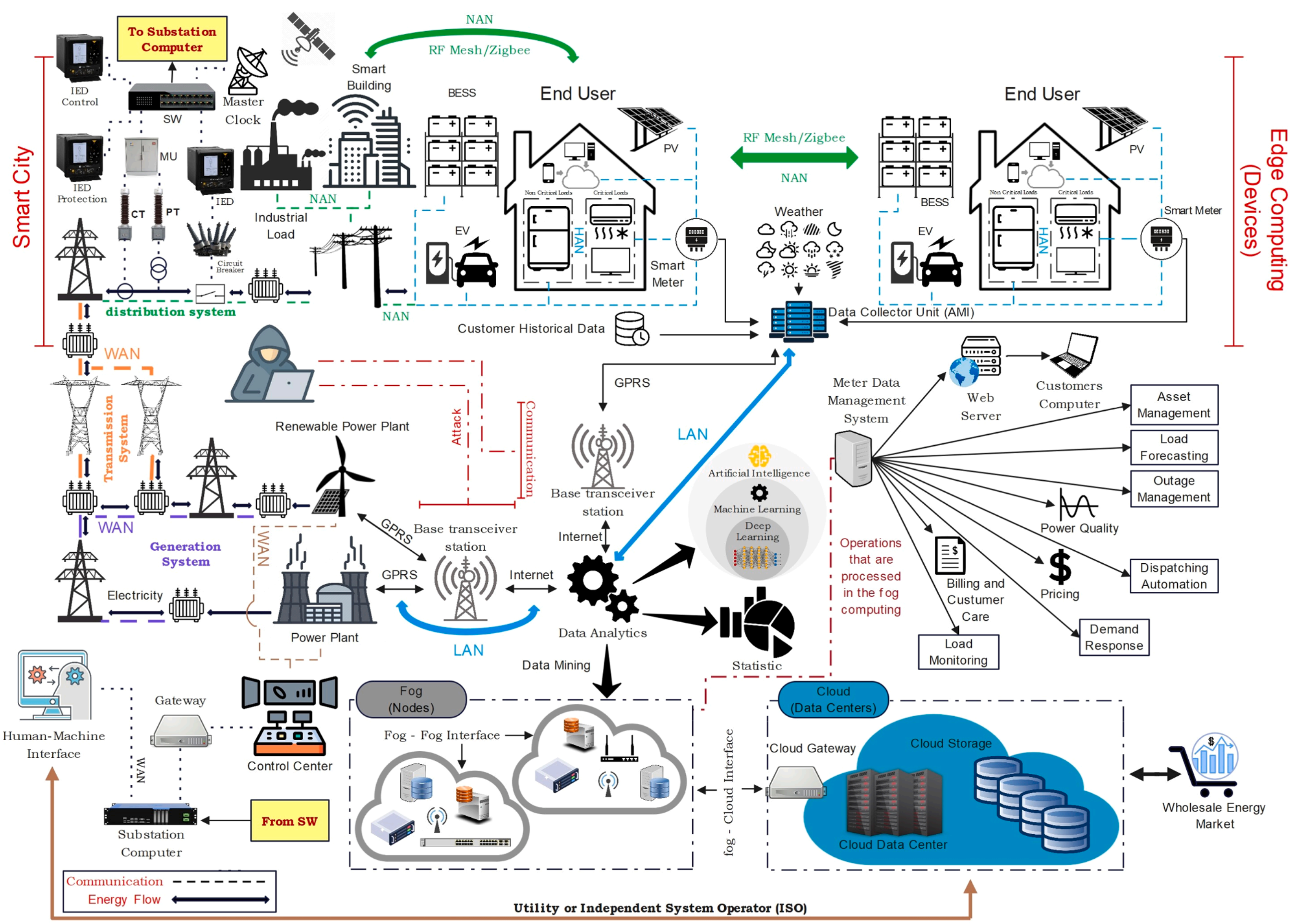

Fig. 5. The Structure of the Cyber-Physical-Social Power System.

10.4. Comprehensive framework proposal

We propose a unified framework that encapsulates the following elements:

- AI Integration: Implementing AI-driven analytics and control mechanisms to enhance system responsiveness and efficiency.
- Data Architecture: Designing scalable and secure data infrastructures that facilitate seamless data exchange and support AI functionalities.

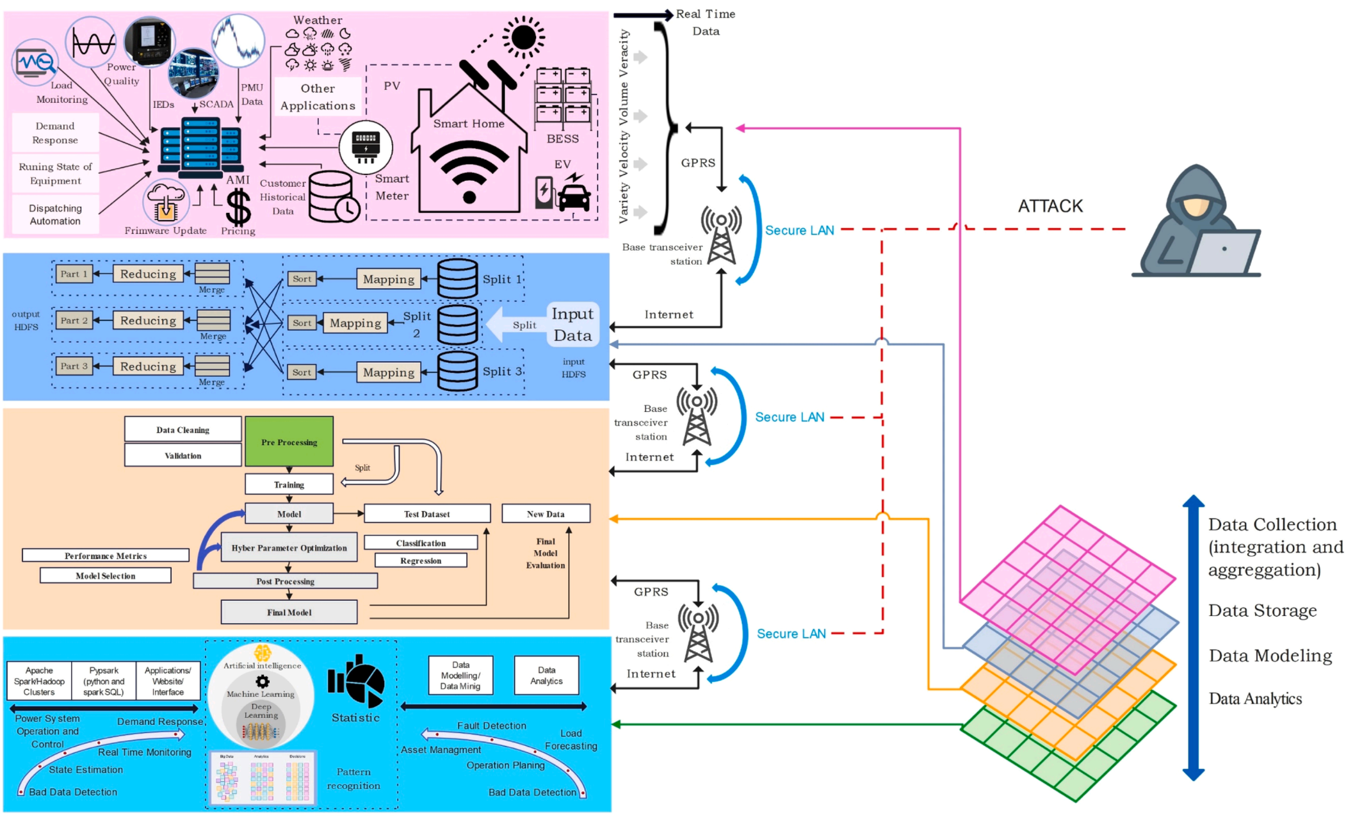

Fig. 6. Architecture of big data management.

- Cybersecurity Measures: Establishing robust security protocols to protect against cyber threats and ensure data integrity.

This integrated approach acknowledges the symbiotic relationship between these components, promoting a resilient and adaptive power system infrastructure.

10.5. Digital humanity and cognitive variables

Incorporating human-centric considerations, such as user behavior, perception, and cognitive responses, is essential in designing and operating these systems (Li et al., 2024c; Lee et al., 2024; Girau et al., 2024). Understanding the human element facilitates the development of intuitive interfaces and protocols that align with societal needs and expectations. This human-centric approach ensures that technological advancements are both practical and ethically sound.

10.6. Recent developments in AI and cybersecurity for critical infrastructure

Integrating AI into critical infrastructure has garnered significant attention, prompting the development of frameworks to ensure its safe and secure deployment (Habibi et al., 2022a, 2021a, 2022b; Hasan et al., 2024; Habibi et al., 2021b; Gaba et al., 2024; Islam et al., 2022). In November 2024, the U.S. DHS released the "Roles and Responsibilities Framework for AI in Critical Infrastructure," guiding the responsible use of AI across essential services.

This framework emphasizes the need for robust cybersecurity measures to protect AI systems from potential threats, recognizing that while AI offers substantial benefits in enhancing efficiency and decision-making, it also introduces new vulnerabilities. The DHS underscores the importance of collaboration between industry and civil society to advance the responsible use of AI in America's critical infrastructure.

Additionally, the CISA released its first Roadmap for AI, guiding efforts to manage the risks and harness the opportunities posed by AI in cybersecurity. This roadmap is part of a broader government effort to ensure the secure development and implementation of AI capabilities.

10.7. Control and management of smart grids in case of lack of observability, and the role of AI

Smart grids represent the evolution of traditional power systems, integrating advanced communication, control technologies, and renewable energy sources to enhance efficiency and reliability. However, maintaining observability and having complete visibility in the system's state remains a critical challenge, especially with the increasing complexity of the grid. Some approaches have been proposed for analyzing the power system in the case of enough observability (Baghaee et al., 2016, 2017a, 2017a, 2018a, 2017b, 2018a, 2018b). In scenarios where observability is compromised due to sensor failures, communication issues, or cyber threats, the control and management of smart grids become increasingly complex. AI and ML technologies play a pivotal role in addressing these challenges by:

- Enhancing Situational Awareness: AI algorithms can process vast amounts of data from various grid components to detect anomalies, predict potential failures, and provide real-time insights, compensating for limited observability.
- Optimizing Grid Operations: ML models can optimize power flow, manage DR, and facilitate the integration of renewable energy sources, ensuring efficient grid operation even with incomplete data.
- Improving Fault Detection and Restoration: AI-driven analytics can swiftly identify fault locations and suggest optimal restoration strategies, minimizing downtime and enhancing grid resilience.

However, deploying AI in smart grids must be cautiously approached. Ensuring data integrity, implementing robust cybersecurity measures, and adhering to ethical guidelines are essential to prevent adversarial attacks and maintain system reliability. The DHS framework provides a foundation for responsible AI integration into critical infrastructure.

Summing up, the architecture of big data-based data-driven management illustrates the comprehensive framework used for handling vast amounts of data generated by smart grids is illustrated in Fig. 6. This framework highlights the key components, such as data storage systems, processing units, and communication networks, that ensure efficient data flow, storage, and analysis, which are critical for real-time decision-making and grid optimization.

11. Conclusions and future trends of the research

Integrating AI with smart grids and critical infrastructure offers a transformative vision for managing and optimizing energy systems. AI can turn grids into self-healing, autonomous systems capable of adapting to demand fluctuations, incorporating renewable energy sources, and improving energy distribution in real-time. These advancements can potentially address current challenges, such as rising energy demands and the need for sustainable solutions. However, achieving these advancements requires overcoming significant challenges, including ensuring data integrity, reducing cybersecurity risks, and developing resilient AI models capable of handling adversarial threats.

On the other hand, future research must adopt a comprehensive approach that simultaneously addresses the integration of AI, cybersecurity, and human factors in smart grid management. The development of AI-based systems should focus on transparency, fairness, and accountability to prevent challenges such as data privacy violations and security threats. International collaboration between academia, industry, and regulatory bodies will be crucial in establishing standards and best practices. By addressing the complexities of data, security, and ethics, energy infrastructures can be made more resilient, sustainable, and efficient, ready to face future challenges.

11.1. The future trends of research

Integrating AI with smart grids and critical infrastructure is poised to shape the future of energy systems in transformative ways. As the demand for smarter, more efficient, and sustainable energy solutions continues to grow, several key trends are expected to drive the future of research in this field. Below are some of the critical trends that will likely define the future of AI-driven smart grid management and cybersecurity in critical infrastructure:

11.1.1. Increased integration of AI in smart grids

AI will play an even more prominent role in smart grid operations, moving beyond basic predictive analytics to fully autonomous systems. Developing self-healing grids powered by AI will enable real-time detection, diagnosis, and repair of faults without human intervention. Advanced AI algorithms can predict demand fluctuations, optimize energy storage, and improve load balancing across diverse energy sources, especially when integrating renewable energies into the grid. These capabilities will enhance grid resilience and adaptability, ensuring efficient energy distribution even in limited observability or external disruptions.

11.1.2. Use of Physics-informed machine learning

PIML is expected to play a pivotal role in the future of smart grids. By combining the strengths of ML with physical laws governing energy systems, PIML can improve the accuracy of models used for power system optimization, fault detection, and load forecasting. This approach can potentially reduce reliance on synthetic data and adversarial examples, which have been a concern in training AI models. PIML will provide more reliable models by embedding physical constraints directly into the learning process, thus improving their robustness and interpretability.

11.1.3. Data-driven smart grid management in the face of cybersecurity challenges

As the digitalization of the energy grid progresses, so will the sophistication of cyber threats target critical infrastructure. Future research will focus on developing AI-driven cybersecurity measures that can proactively identify vulnerabilities in smart grids, detect real-time threats, and respond to security breaches autonomously. The study will also explore blockchain technology to ensure data integrity and secure transactions across distributed energy systems. The challenge will be integrating these technologies with minimal latency while providing data privacy and compliance with regulatory standards.

11.1.4. Adversarial AI and the role of synthetic data in model training

As the use of AI in smart grids grows, there will be increasing attention on adversarial AI, deliberate manipulations of AI systems designed to exploit vulnerabilities for malicious purposes. In response, the research community must develop more resilient AI models to detect and mitigate adversarial attacks. One promising direction is using synthetic data generation techniques to create diverse training datasets for AI models, including edge cases and rare events. This approach can help improve model robustness, mainly when real-world data is sparse or incomplete.

11.1.5. AI-powered digital twins for grid simulation and optimization

Digital twins, virtual replicas of physical assets or systems, are rapidly emerging as a key technology for simulating and optimizing grid operations. Future research will focus on creating AI-powered digital twins to provide real-time insights into grid performance, enabling dynamic simulations for predictive maintenance, risk management, and operational decision-making. These digital twins will simulate grid conditions and autonomously adjust system parameters to optimize performance and energy consumption.

11.1.6. Human-centric AI and cognitive systems

The future of AI in smart grids will increasingly involve a human-centric approach that integrates human decision-making with machine intelligence. AI systems will incorporate cognitive computing techniques to understand human behavior, predict consumer demand, and enable more intuitive interactions between operators and the grid. Moreover, research will explore how to effectively incorporate perception and cognitive variables (e.g., human decision-making) into AI models to improve system responsiveness and adaptability.

11.1.7. Edge and fog computing for real-time data processing

The need for faster data processing at the network’s edge will drive the development of more advanced edge and fog computing solutions. By decentralizing data processing, these technologies will enable smart grids to make real-time decisions locally, reducing latency and the risk of network congestion. The research will focus on developing AI algorithms that can operate efficiently in these environments, ensuring they can process large volumes of data in real-time while maintaining security and reliability.

11.1.8. Collaboration between AI, IoT, and big data analytics

The future of smart grid management will see greater integration of AI, IoT devices, and big data analytics. IoT sensors will collect vast amounts of data from various grid components, which will then be analyzed using AI-driven analytics to provide actionable insights. This collaboration will enable more proactive grid management, improved DR, and faster fault detection. The challenge will lie in managing the vast amounts of data generated by IoT devices while ensuring their accuracy, security, and real-time processing.

11.1.9. Sustainability and environmental considerations

As smart grids evolve, sustainability will remain a key focus. Future research will explore the role of AI in optimizing energy consumption and reducing carbon emissions. AI systems will be employed to integrate better renewable energy sources, such as solar and wind, into the grid, reducing dependence on fossil fuels. AI-driven optimization models will be essential for reducing energy waste and ensuring that power systems operate in an environmentally responsible manner.

11.1.10. Regulatory and ethical implications of AI in energy systems

As AI plays a central role in managing critical infrastructure, researchers will increasingly address the ethical and regulatory challenges associated with AI deployment. This includes ensuring that AI models are transparent, explainable, and fair, and addressing concerns around data privacy, bias, and accountability. Research will focus on developing frameworks and standards that balance innovation with the need for ethical considerations, ensuring that AI contributes positively to the long-term goals of energy system optimization and sustainability.

11.2. Conclusion and final remarks

Integrating AI with smart grids and critical infrastructure represents a transformative shift in how energy systems are managed, optimized, and secured. The convergence of AI and cutting-edge technologies offers immense potential to enhance these systems' efficiency, reliability, and resilience. By harnessing the power of AI, smart grids can evolve into self-healing, autonomous systems capable of adapting to fluctuations in demand, integrating renewable energy sources, and improving overall operational efficiency. However, realizing the full potential of these advancements requires continued research and a concerted effort to address critical challenges related to data integrity, cybersecurity, and adversarial attacks.

As AI and ML continue to shape the evolution of critical infrastructure, future research must prioritize a holistic approach that incorporates not only technological innovation but also ethical considerations, human factors, and the secure integration of emerging technologies. The risks posed by adversarial AI and cyber threats necessitate the development of resilient, secure, and transparent AI systems that can withstand malicious attacks while ensuring data privacy and system reliability. Furthermore, AI models should be designed to be explainable, fair, and accountable, addressing concerns about bias, transparency, and the impact of these technologies on society.

In addition to technological and security advancements, there is a growing need for collaboration between academia, industry, and regulatory bodies. We can ensure that AI-driven solutions are deployed responsibly and effectively by fostering cross-sector partnerships. Implementing frameworks such as the DHS framework and CISA's AI roadmap highlights the importance of establishing clear standards and best practices for AI deployment, especially in high-stakes environments like energy systems. These efforts will ensure that AI contributes to the sustainable development of critical infrastructure without compromising security or ethical values.

Moreover, the future of smart grids must also account for integrating human and cognitive elements within the system. AI should be a tool for automation, enhance human decision-making, and create a more collaborative relationship between operators and the system. The role of human-centric AI—which considers human behavior, cognitive processes, and decision-making—will become increasingly important as AI systems interact with grid operators, consumers, and other stakeholders.

In conclusion, the future of smart grid management lies in successfully integrating AI, cybersecurity, and human factors, creating a balanced and adaptive framework that can handle the complexities of modern energy systems. By prioritizing these areas and addressing the challenges associated with data, security, and ethics, we can build a more resilient, sustainable, and efficient energy infrastructure that meets the demands of an increasingly interconnected and dynamic world. The continued evolution of AI in critical infrastructure promises to optimize performance and ensure that energy systems remain robust, secure, and capable of responding to future challenges. Overall, our findings reaffirm that AI/ML and cybersecurity must be co-designed with the data architecture of CPS DNs to ensure resilient, secure, and ethical deployment.

CRediT authorship contribution statement

Baghaee Hamid Reza: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kiarash Pourramezani:** Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **B. Gharehpetian Gevork:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis.

Declaration of Competing Interest

The authors have no conflict of interest.

Acknowledgements

This work is based upon research funded by Iran National Science Foundation (INSF) under project No. 4030297.

Data availability

No data was used for the research described in the article.

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