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Review

Applied Control and Artificial Intelligence for Energy Management: An Overview of Trends in EV Charging, Cyber-Physical Security and Predictive Maintenance

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Abstract: On 28 February–2 March 2023, the 2023 States General of Artificial Intelligence (AI) event was held in Italy under the sponsorship of several multinational companies. The purpose of this event was mainly to create a venue for allowing international protagonists of AI to discuss and confront on the recent trends in AI. The aim of this paper is to report on the state of the art of the literature on the most recent control engineering and artificial intelligence methods for managing and controlling energy networks with improved efficiency and effectiveness. More in detail, to the best of the authors' knowledge, the scope of the literature review considered in this paper is specifically limited to recent trends in EV charging, cyber-physical security, and predictive maintenance. These application scenarios were identified in the above-mentioned event as responsible for triggering most of the business needs currently expressed by energy companies. A critical discussion of the most relevant methodological approaches and experimental setups is provided, together with an overview of the future research directions.

Keywords: EV charging; load altering attacks; predictive maintenance

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1. Introduction

The aim of this paper is to provide an overview of the recent literature on control engineering and artificial intelligence methods that improve the efficiency and effectiveness of managing and controlling energy networks. More in detail, to the best of the authors' knowledge, the scope of the literature review considered in this paper is specifically limited to recent trends in:

- EV charging,
- cyber-physical security, and
- predictive maintenance,

as these were identified as the contexts which most of the business needs of energy companies currently revolve around.

Indeed, on 28 February–2 March 2023, the 2023 States General of Artificial Intelligence (AI) [1] event was held in Italy under the sponsorship of several multinational companies with the aim of creating a venue for allowing international protagonists of AI to discuss and confront the recent trends in AI. With respect to the management and control of energy networks, the participation of Terna, Enel Group, Snam and eVISO in this event was particularly relevant.

In order to work effectively and efficiently, the overall power system must be able to ensure the balance between power production and consumption at all times, while dealing with unexpected events in terms of supply and demand. This implies the necessity to rely on flexible resources that prove capable of modulating production as a result of the actual power needs. Applied control and AI offer the best methodological framework today for tackling the emerging business need for innovative solutions that meet flexibility and adequacy requirements, especially as renewable energy sources are being progressively exploited in replacement of traditional thermoelectric power stations. The technology of energy storage systems deserves particular mention as, in such a context, it allows for the storage of the surplus energy produced and return it to the system when needed. When combined with renewable energy plants, this can provide a source of energy that is not only clean, but also flexible and reliable.

1.1. Motivation

There exist several review papers focusing on control-driven and AI-driven energy management. Among them, some of the most recent and cited are listed in Table 1.

Table 1. Recent review papers focusing on control-driven and AI-driven energy management.

Review Paper Title	Challenges Discussed	Reference
Artificial intelligence techniques for photovoltaic applications: a review	Enabling fault tolerance in photovoltaic systems—namely, forecasting and modeling of meteorological data, sizing of photovoltaic systems and modeling, simulation and control of photovoltaic systems—via AI, exploiting their capability in terms of symbolic reasoning, flexibility and explanation	[2]
A review of extremely fast charging stations for electric vehicles	Current technology gaps in EV fast charging stations, ranging from infrastructure through power electronics to extremely fast charging	[3]
Application of machine learning for wind energy from design to energy-water nexus: a survey	Using AI and in particular neural networks for wind energy technology, namely wind speed prediction, design optimization, fault detection, optimal control and maintenance planning	[4]
A comprehensive survey on the role of artificial intelligence in solar energy processes	Using AI—artificial neural networks, fuzzy logic, hybrid systems, wavelets and genetic algorithms—for the simulation and estimation of renewable energy performance management, in order to improve photovoltaic power generation	[5]
Artificial intelligence implications on energy sustainability in Internet of Things: a survey	Integrating machine learning and swarm intelligence for the design of innovative protocols aimed at predicting and forecasting demand and at optimizing energy use based on the availability of a massive number of Internet of Things devices	[6]
A review of denial of service attacks and mitigation in the smart grid using reinforcement learning	Exploiting reinforcement learning for detecting and mitigating denial of service attacks in smart grids, providing a detailed analysis of the strengths and limitations of current approaches as well as of prospects for future research	[7]

Yet, to the best of the authors' knowledge, this is the first survey paper that provides a comprehensive state-of-the-art review of the most recent methodologies and techniques addressing the business needs that the largest energy companies in Italy are currently facing.

Such business needs are: cost-effective charging of electric vehicles in service areas, enabled by applied control; cyber-physical system security, especially in terms protection against load-altering attacks; AI-driven predictive maintenance and anomaly detection in energy management, especially as regards aerial reconnaissance of electric poles in the power grid, robust anomaly detection in photovoltaic production plants and horizontal axis wind turbines, and learning the behavioural profiles of consumers for estimating power demand in distribution networks.

We claim to offer a new perspective on the topic, namely by (i) highlighting the relevance of using ESS and applied control to compensate for power peak loads in EV charging stations as well as for load-altering attacks in smart grids and power transmission networks, and by (ii) stimulating the attention of the research community on a few application scenarios of predictive maintenance where applied AI is playing a decisive role (see Section 4 for more details in this respect).

1.2. Paper Structure

The paper is organized as follows, in order to critically explore the relevant energy network scenarios where applied control and AI are expected to yield significant benefits.

Section 2 reviews the recent literature targeting the problem of cost-effective charging of electric vehicles in service areas, even in the presence of renewable energy sources and energy storage units.

Section 3 reviews the recent literature targeting the problem of cyber-physical system security, with specific reference to defense schemes against load-altering attacks in power transmission networks.

Section 4 is devoted in general to reviewing the recent literature on predictive maintenance and anomaly detection in energy management. Namely, Section 4.1 focuses on the problem of aerial reconnaissance of electric poles in power grids for maintenance and surveillance purposes. Section 4.2 focuses on robust anomaly detection in photovoltaic production plants. Section 4.3 focuses on anomaly detection in horizontal axis wind turbines. Section 4.4 focuses on the data-driven estimation of current and ampacity on high-voltage overhead lines. Section 4.5 focuses on AI for learning the behavioural profiles of power consumers as relevant insight for estimating power demand in distribution networks.

Section 5 proposes a brief discussion of the reviewed literature, highlighting the limitations of existing methods and future directions. Concluding remarks end the paper.

2. Cost-Effective Charging of Electric Vehicles in Service Areas

In order to help electric vehicles (EVs) reach ubiquity, EV charging companies and governments should ensure that the availability of fast charging infrastructure does not turn out to be a bottleneck for growth, especially as the most recent projections suggest that EVs will amount to 75% of new car sales by 2030. In response to that, the Bipartisan Infrastructure Law signed by US President Joe Biden on 15 November 2021 provides $7.5 billion to develop the country's EV charging infrastructure, with the specific goal of installing, nationwide, 500,000 publicly accessible charging stations compatible with all vehicles and technologies by 2030. It is therefore time for EV charging companies to focus on:

- investing in production capacity and a skilled workforce;
- using data and analytics for network planning purposes;
- reducing "range anxiety" of EV drivers.

Investing in production capacity and skilled workforce will enable EV charging companies to scale, thus laying the foundations for successful rollouts of charging stations in the coming years. Indeed, significant investments will be required to develop a pervasive recharging infrastructure, which is safely and efficiently integrated into the electrical energy system. In particular, intelligent power management in service areas for EV charging with minimum time shall be key to the above-mentioned scaling effort. Sophisticated data-driven planning will be required to identify the best sites for an effective in-demand charging network. Eventually, such a successful infrastructure will boost the confidence of EV drivers which is currently still undermined by range anxiety.

More in detail, with specific reference to the scope of production capacity, there is an emerging need for control strategies aimed at efficiently operating a service area equipped with fast charging stations for plug-in electric vehicles (PEVs), with renewable energy sources, and with an electric energy storage system (ESS). The control requirements expressed by operators of such service areas revolve around the need for avoiding peaks in the power flow at the point of connection (POC) with the distribution grid, while providing EV charging in minimum time, as well as mitigating congestion and preserving stability, also assuming the presence of uncertainty in the charging power demand and generation. In this respect, in [8,9], a service area for PEVs is defined as the electromobility equivalent of a traditional petrol station, implying the presence of several charging stations offering fast charging to the arriving PEVs. An example of a service area for PEVs is provided in Figure 1.

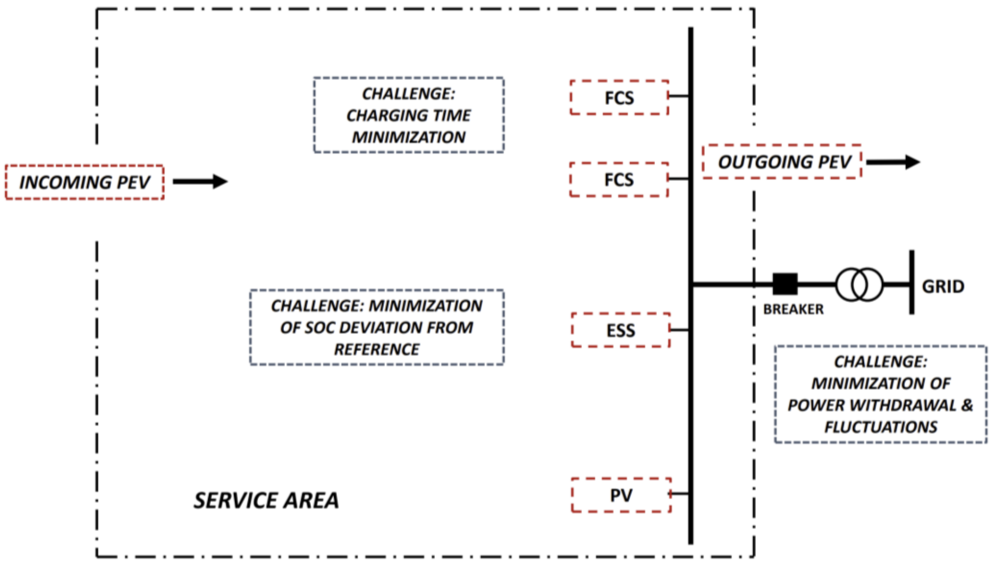

Figure 1. Reference scenario for Section 2, consisting in a service area in which a fast-charging station (FCS), a photovoltaic panel (PV) and an ESS are included. The FCS allows for the charging of the PEVs at different power levels. The power coming from the PV is stored in the ESS. The ESS releases power during the charging sessions. The grid structure is reduced to the POC and modeled as an infinite bus.

The requirement for fast charging to achieve acceptable recharge times for drivers implies the necessity for high power levels. However, having only a few fast-charging sessions simultaneously can lead to a significant increase in power flows between the point of connection (POC) of the service area and the distribution grid, resulting in high operating costs for the service area.

To address this issue, one approach is to introduce a stationary energy storage system (ESS) that helps mitigate the strain on the grid by reducing the peak power demand from plug-in electric vehicles (PEVs). Another effective solution is to incorporate renewable power generators to provide clean energy for PEV charging, which also helps alleviate power peaks at the POC. However, the effectiveness of the ESS in mitigating power peaks depends on its state of charge and capacity. Additionally, it is crucial to consider and manage the uncertainties associated with both PEV power demand, which depends on the arrival times and charging requests of individual vehicles, and renewable power generation.

Various control methodologies have been proposed in the literature to tackle the service area control problem. These include continuous-time control methods based on variational calculus and Pontryagin's minimum principle (PMP) [10–13], as well as discrete-time approaches primarily based on model predictive control (MPC) [14–16].

In [17], Di Giorgio et al. propose a stochastic MPC algorithm for controlling a service area equipped with an ESS and renewable energy generators. This algorithm utilizes the ESS to balance ongoing charging sessions, ensuring that the ESS does not deplete completely during operation. It also modulates the charging power provided to PEVs to track their requested power as closely as possible, aiming to minimize charging time and reduce operational costs as a result. While in [18] a continuous-time closed loop and closed-form solution based on PMP theory is proposed for the controller, in [17], instead, the problem is solved via MPC, extending the formulation with the modelisation of ESS power losses and with control flexibility on the power set point of recharging sessions—namely, this can be reduced at times of significant congestion.

Unlike Ref. [19], which presents a deterministic MPC-based solution with no flexibility on the charging power, Ref. [17] allows for stochastic MPC and flexible charging sessions. The authors assume that the expected value of the PEVs' power demand is known to the service area operator, which can be estimated from historical data. This assumption overcomes the limitations of deterministic MPC, which requires accurate knowledge of demand profiles. Additionally, the strategy proposed in [17] exploits the MPC objective function in order to be particularly effective at modulating the charging power offered to the PEVs in periods of extreme congestion of the service area, and is, as of today, the first study that simultaneously addresses (a) power flow regulation at the POC, (b) stabilization of the ESS state of the charge and (c) uncertain power reference tracking.

Kucevic et al. [20] propose a coordinated control approach using linear optimization for a group of ESSs located at different charging stations. This approach reduces the charging peak power, even with a high number of PEVs. They also require knowledge of the expected power demand of the PEVs, which can be derived from historical data.

In [21], Ding et al. show that an ESS can reduce the peak power at the POC with the distribution grid when several electric buses are charging at the same time and propose a control strategy aimed at optimal sizing and management of said ESS. By contrast with the above-mentioned exact solving methods, Sun et al. propose in [22] a heuristic solution to the problem of optimal power scheduling with minimum cost and pollution in fast EV charging stations interconnected with wind, PV power and an ESS. Leonori et al., instead, excluded a priori MPC methods in [23], claiming they are significantly dependent on prediction accuracy, and proposed an energy management system based on a fuzzy logic controller to cope with the stochastic nature of public fast charging demand in a grid-connected nanogrid.

In [24], Huang et al. pursue deterministic cost minimization for controlling the power flows in a grid with charging stations, renewable plants and ESSs. In [25] Chen et al. propose a rule-based control scheme to manage and control a service area characterized by the presence of hydrogen production and storage facilities, with a specific focus on maximizing the use of locally produced clean energy. In [26], the same problem is addressed via linear optimization-based and deterministic MPC, with the specific aim at reducing the operational emissions. In [27], the problem of optimal planning of the location, number and dimension of ESS devices, renewable plants and charging stations is addressed with the aim of minimizing the operating costs of the charging infrastructure.

From a different perspective, Jang et al. in [28] propose a grid-connected inverter for photovoltaic-powered EV charging stations. In [29], Ye et al. propose to determine the optimal charging schedule due to the uncertain arrival time and charging demands of EVs according to a reinforcement-learning based scheme which is proven to outperform the baseline MPC-based one. Instead, in [30], two control strategies resulting from the combination of maximum sensitivity selection and a suitably designed genetic algorithm are presented and reviewed with respect to the problem of fast EV charging in a smart grid.

Overall, in Section 2, the most common challenges related to charging electric vehicles in service areas were identified: among different applied control approaches, MPC is considered as the most promising technique for tackling the problem of cost-effective charging in service areas, assuming the additional presence of an ESS for mitigating peak power requests from the PEVs.

For the sake of clarity and readability, in Table 2 we recap the references in Section 2, distinguishing between the challenge faced and the methodological approach chosen to tackle each challenge.

Table 2. Literature review relative to cost-effective charging of electric vehicles in service areas.

Challenge Faced	Methodological Approach	Reference
Service area control problem	Continuous-time calculus of variations (PMP)	[10–13]
Service area control problem	Discrete-time controller (MPC)	[14–16]
Fast charging service area	Optimal control of an ESS via PMP (continuous-time)	[18]

Table 2. *Cont.*

Challenge Faced	Methodological Approach	Reference
Fast charging service area	MPC, assuming perfect knowledge of the future charging demand	[19]
Fast charging service area	Stochastic MPC with minimization of the power flow at the POC, without assuming perfect knowledge of the future charging demand	[17]
Urban distribution grids with a high share of PEVs	Reducing charging peak power by controlling a certain number of ESS via linear optimization	[20]
Charging station for electric buses	Optimal sizing and management of an ESS (ESS control)	[21]
Fast EV charging stations with wind, PV power and ESS	Sub-optimal heuristic power scheduling strategy to minimize costs and pollution	[22]
Public fast charging station in a grid-connected nanogrid	Energy management system based on a fuzzy logic controller to tackle the stochastic nature of fast charging demand	[23]
Smart grid with charging stations, renewable plants and ESSs	Deterministic cost minimization for power flow control	[24]
Service area control in the presence of hydrogen production and storage facilities	Rule-based control scheme with maximization of locally produced clean energy	[25]
Service area control in the presence of hydrogen production and storage facilities	Linear optimization-based deterministic MPC	[26]
Smart grid with charging stations, renewable plants and ESSs	Minimizing operating costs with optimal planning of location, number and dimension of ESS devices, renewable plants and charging stations	[27]
Photovoltaic-powered EV charging station	Grid-connected inverter	[28]
Service area control problem	Reinforcement-learning-based optimal charging schedule with uncertain arrival time and charging demands of EVs	[29]
Fast charging service area	Control strategy based on the combination of maximum sensitivity selection and a suitably designed genetic algorithm	[30]

3. Cyber-Physical System Security

Power systems have been evolving towards tightly interconnected cyberphysical systems where a modern ICT control system manages the dynamics and operational constraints of the underlying physical network (see Figure 2 for an example). Indeed, the unique interdependencies between physical plants and cyber infrastructures characterizing the electric power industry make companies vulnerable to several exploitation threats, such as billing fraud with wireless smart meters and the commandeering of some specific devices to stop operating plants, up to physical destruction. This implies critical risks in terms of security. Consequences may include power outages, destruction of equipment and damage to single or groups of devices throughout the grid.

Data tampering can lead to severe consequences if proper fail-safe measures are not in place to mitigate its impact. It is common for operators to rely solely on data from monitoring systems to regulate power flow without manual validation or dedicated protocols to ensure data integrity. This is primarily due to these systems not directly contributing to utility value streams and being susceptible to cost-cutting measures or outdated security standards. However, such practices create opportunities for malicious exploitation, as highlighted in [31].

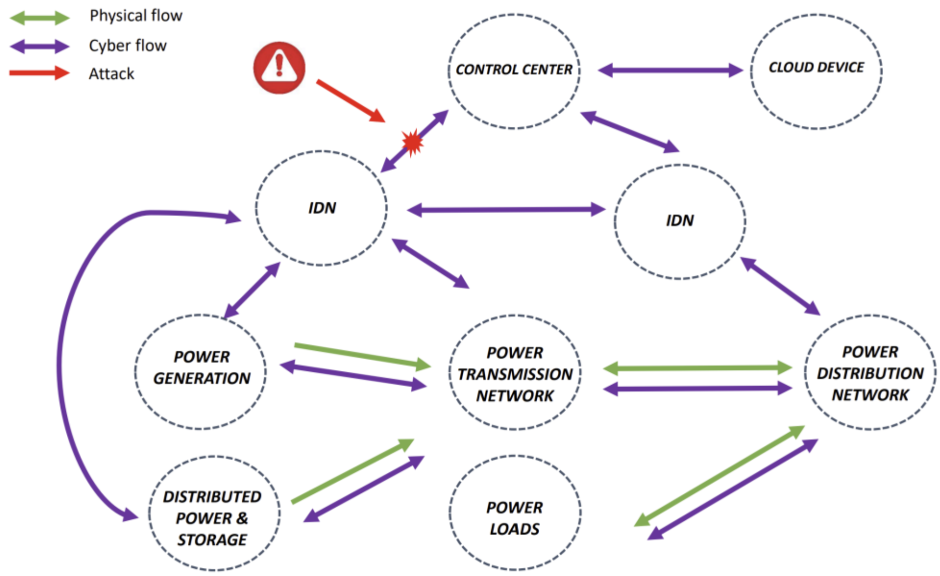

Figure 2. Reference scenario for Section 3, showing the operation flow in a generic smart grid. The transmission channel between the control center and each device is the place that happens to be the most vulnerable to attacks.

Another critical aspect that cannot be overlooked is physical security. Inadequate access controls and unsecured panels for network assets or plants provide attackers with physical access to significant portions of the power system, compromising the integrity of sensitive locations such as data centers and generation, transmission and distribution sites.

In [32], a proposed cyber-physical security framework and advanced tools aim to address vulnerabilities and respond in a timely manner to threats. This architecture bridges the gap between computer science and control-theoretic approaches, specifically addressing the challenges posed by the Industrial Internet of Things. Reference [33] provides a review of potential attack vectors and outlines cybersecurity requirements. They propose a layered approach to evaluate cyber-physical risks.

This section focuses on load altering attacks, as defined in [34,35]. Load-altering attacks (LAAs) target demand response and demand-side management programs, aiming to control and manipulate specific unsecured controllable loads to cause grid damage, circuit overflow or other adverse effects. In a smart grid, attackers can launch direct load altering attacks by injecting false commands into aggregators responsible for load control. By remotely manipulating loads, attackers can disrupt the system by causing deviations in operating frequency. Reference [36] provides an overview of these cyber-intrusion plans, demonstrating how attackers alter loads via the Internet and distributed software agents. Defense mechanisms tested on the IEEE 24-bus test system prove effective in reducing the cost of load protection while ensuring no overload occurs due to ongoing attacks.

In [37], dynamic LAAs are discussed, focusing on attacks that not only aim to change the load amount but also control the trajectory of load changes over time. Dynamic LAAs are feedback-based attacks that maliciously compromise and dynamically control flexible loads used in demand-side management programs and other smart functions, with the intention of destabilizing the power transmission network. Simulation scenarios based on a six-bus test system demonstrate how dynamic LAA trajectories can render the overall power system unstable.

A systematic review of dynamic LAAs is presented in [34] by Amini et al. They classify these attacks based on open-loop versus closed-loop, single-point versus multi-point, feedback type and attack controller. The study formulates and analyses a specific closed-loop dynamic LAA that targets power system stability. A defense system is designed to mitigate the effects of the attack by solving a non-convex pole-placement optimization problem. The defense scheme assumes uncertainty in the attack sensor location and is evaluated through a simulation using the IEEE 39-bus test system.

While Amini et al.'s defense scheme aims to secure loads and limit attacker capabilities, Ref. [38] proposes a different control law focused on managing active components of the grid, specifically optimally placed energy storage systems (ESSs). Using Lyapunov arguments, this approach protects power transmission networks against closed-loop dynamic LAAs by controlling ESSs to compensate for destabilizing effects. Real-time detection or attack reconstruction is not required, assuming complete knowledge of the attack characteristics. Simulation results highlight the relevance of using ESSs to support primary frequency regulation.

Furthermore, ESSs are meant to play a vital role in protecting power networks from cyber-physical attacks and are becoming integral parts of modern power networks. Their flexibility in absorbing or releasing power in a controlled manner enables the provision of ancillary services, improving power quality and voltage stability while optimizing the use of renewable energy sources. Reference [39] extends the previously proposed approach to a robust control strategy that optimally places ESSs to protect the power transmission network against various dynamic LAAs. In [40], an extensive description of the dynamics of the control actions and their effects in different network scenarios is provided with the support of numerical simulations.

In [41], Xun et al. present the perspective of a malicious entity conducting a direct LAA by continuously manipulating aggregators to maximize the impact. The authors highlight the difficulty of detecting such attacks, as attackers can inject false data to contaminate feedback from aggregators to controllers. They propose a three-step optimization method to determine the optimal sequence of successive LAAs based on the analysis of frequency changes induced by the attacks.

Load-altering attacks can also affect power generation. The automatic generation control mechanism in power generators is vulnerable to such attacks. Ref. [42] examines a scenario where cyber attackers remotely alter the power consumption of multiple electric loads in power distribution systems, compromising the automatic generation control mechanism. They propose an attack-thwarting system that adjusts the power consumption of flexible loads in real-time in response to frequency disturbances caused by load altering attacks.

In [43], false data injection attacks in a cyber-physical power system compromise a subset of frequency control signals, with two possible configurations: location-fixed or location-switching. The study determines optimal switching conditions and partial feedback attack matrices for selecting the best attack locations. A case study using the IEEE 9-bus test system demonstrates the approach. Ref. [44] presents distressing attacks resulting from coordinated malware-infected IoT units, which are employed to synchronously turn high-wattage appliances on or off, affecting the grid's primary control management. The impact of the attack depending on the power plant type is extensively studied. Ref. [45] provides additional recent approaches for designing optimal LAAs.

In general, in Section 3, the recent literature targeting the problem of cyber-physical system security was reviewed. Specific focus was placed on defense schemes against LAAs in power transmission networks.

The reference scenario for Section 3 was that of smart grids and power transmission networks as depicted in Figure 2. Yet, for the sake of completeness, we report that in [46], a review of the most relevant cyber-physical security challenges with respect to the reference scenario of Section 2 (namely, electric vehicle charging) is also provided.

For the sake of clarity and readability, in Table 3 we recap the references in Section 3, distinguishing between challenges faced and the methodological approach chosen to tackle each challenge.

Table 3. Literature review relative to cyber-physical system security, with specific reference to defense schemes against load-altering attacks in power transmission networks.

Challenge Faced	Methodological Approach	Reference
Industrial automation and control systems (IACSs).	Security framework and advanced tools to properly manage vulnerabilities, and to react in a timely manner to the threats	[32]
Cyber infrastructure security	Layered approach for evaluating risk based on the security of both the physical power applications and the supporting cyber infrastructure	[33]
Power transmission grid affected by dynamic LAAs	Protection system is designed against D-LAAs by formulating and solving a non-convex pole-placement optimization problem	[34]
Designing cyber-physical attacks for destabilizing a smart grid	Formulation of dynamic LAAs as a new class of cyber-physical attacks	[37]
Power transmission grid affected by dynamic LAAs	Managing active components of the grid such as a group of optimally placed ESSs to protect power transmission networks so that any destabilizing effects of dynamic LAAs are compensated without the need for resorting to any real-time detection or reconstruction of the attack, under the assumption that the attack characteristics be completely known a priori	[38]
Power transmission grid affected by dynamic LAAs	Extension of the approach in [32] to a set of identified potential dynamic LAAs	[39]
Power transmission grid affected by dynamic LAAs	Extensive description of the dynamics of the control actions and their effects in different network scenarios provided with the support of numerical simulations	[40]
Generic smart grid subject to internet-based LAAs	Cost-efficient load protection strategy	[36]
Generic smart grid	Optimal switching data injection strategy for a direct LAA is presented to be used from the attacker's perspective	[41]
Power grid harmed by LAAs	Attack-thwarting system for countering LAAs	[42]
Power grid subject to coordinated load-changing attacks	Models to enhance power plant responses to active attacks targeting the energy infrastructure	[44]

4. Predictive Maintenance and Anomaly Detection in Energy Management

One of the biggest emerging critical issues in the exploitation of renewable energy sources is plant maintenance. Maintenance represents a crucial element as it is crucial to ensure that assets are in perfect working order. In fact, failures and breakdowns can generate downtime episodes with costly repairs, up to and including the replacement of entire components, with the consequent effect of leaving thousands of homes powered by fossil fuels for days or weeks. To reduce or prevent plant downtime episodes and cut down related losses, it is crucial to apply smart maintenance strategies, thus anticipating anomalous situations and managing them appropriately. AI has been successfully deployed in renewable energy plants in recent years because of its remarkable ability to anticipate such phenomena: this is exactly where predictive maintenance comes into play.

In the electricity sector, in order to compare the cost of generation from different sources, the so-called levelized cost of energy (LCOE) is calculated according to an internationally recognized methodology. This synthetic indicator represents an economic estimate of the average cost required to finance and maintain a power generation facility over its lifetime, relative to the total amount of energy generated during the same time interval. Specifically, it considers capital costs, fuel costs (if any), fixed and variable operation and maintenance (O&M) costs, financing costs and an assumed utilization rate for each type of plant.

Usually, the cost associated with maintenance is expressed as a percentage of the LCOE. Referring to the report published by the International Renewable Energy Agency

(IRENA) in 2019 [47], O&M costs can be as high as 30% of the LCOE, such as in on-shore wind power plants.

The key to preventing potentially debilitating failure phenomena is their early detection, which was traditionally carried out by monitoring the wear level of components or through scheduled maintenance.

More recent and advanced is predictive maintenance, which proposes a strategic approach aimed at preventing failures before they can occur, minimizing downtime, optimizing production capacity and thus generating productivity gains.

Compared with corrective or reactive maintenance, in which repairs occur when a failure has occurred, or preventive or scheduled maintenance, in which interventions are performed based on the use of a component, predictive maintenance focuses on verifying the health of machinery in order to predict when a failure will occur and prevent it. Ultimately, this makes it possible to resolve the problem before it leads to a downtime episode or component failure.

More in detail, in recent years, especially with the spread of Internet of Things (IoT) technologies in the context of Industry 4.0, AI has been playing a key role in predictive maintenance. Indeed, it enables the optimization of maintenance strategy using predictive models, trained by employing data streams collected from sensor networks placed in renewable energy plants.

For example, as proposed in [48], a neural network can be trained to recognize the proper operation of a plant and predict it in real time. If the model's prediction does not match actual sensor measurements, the AI model generates an alarm to signal an abnormal condition that could lead to a failure and consequently to a plant shutdown event.

The great advantage of AI over traditional maintenance techniques is its data-driven nature. While traditional techniques use rules and control charts that are the result of rigorous plant analysis by domain experts, AI techniques bypass these requirements and feed off data from the field. Thus, armed with a data acquisition system, such as SCADA systems, it is possible to train an AI model that can automate predictive maintenance. Thus, the potential of AI, in particular deep learning, can be harnessed in the domain of energy management similarly to what already happened in other contexts (e.g., [49,50]).

More specifically, according to the framework depicted in Figure 3, the data recorded by the sensors are used to train the AI to recognize, with a certain predictive horizon, abnormal situations that may be precursors of failure phenomena on the plant. The model raises an alarm when the prediction deviates from the actual sensor measurements, allowing management of the anomaly and anticipation of component failures.

Hence, the use of the aforementioned AI techniques by leading O&M companies is producing the benefit of increased reliability and safety in plants. In particular, real-time data processing using predictive analytics tools is making it possible to extend asset lifecycles, reduce repair costs and properly manage abnormal situations.

Overall, as stated both in [49,50], AI makes it possible to:

- reduce unplanned downtime events by up to 12% and
- increase operating margins by 15%.

As significant as these numbers are, it is important to note that there is still considerable room for improvement.

With specific reference to predictive maintenance and anomaly detection as introduced above, the relevant use cases proposed during the 2023 States General of Artificial Intelligence (AI) [1] are the following:

- aerial reconnaissance of electric poles in the power grid for maintenance and surveillance purposes;
- robust anomaly detection in photovoltaic production plants
- anomaly detection in horizontal axis wind turbines;
- data-driven estimation of current and ampacity on overhead lines;
- AI for learning the behavioural profiles of power consumers as relevant insight for estimating power demand in distribution networks.

The following subsections discuss each use case and the related literature in detail.

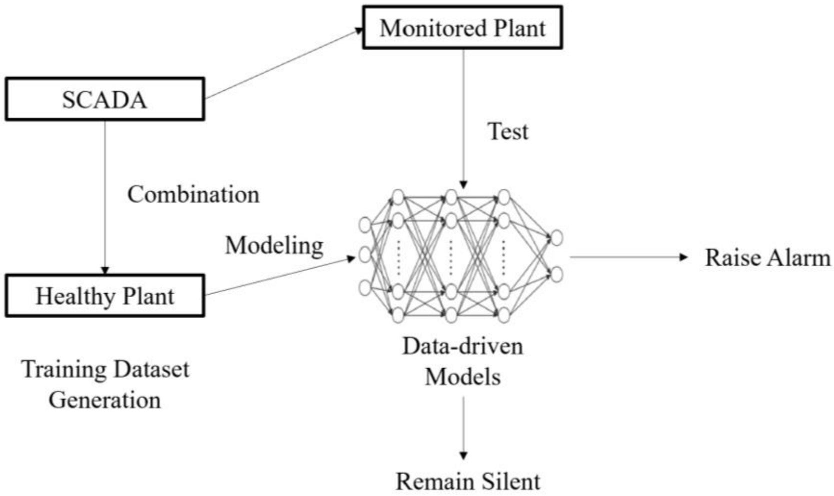

Figure 3. Reference scenario for Section 4, showing the data-driven framework behind predictive maintenance and anomaly detection tools in energy management. First, the training dataset is generated after collecting SCADA (supervisory control and data acquisition) data of healthy plants, as well as cleaning invalid and missing values. Then, through suitable data-driven algorithms, models are developed based on the training dataset for the relevant predictive maintenance or anomaly detection task. Finally, online monitoring on the monitored plant is carried out, with the aim of identifying impending failures based on the prediction errors of the selected model. This implies that an alarm is triggered whenever an anomaly or a fault is detected; otherwise, the monitoring tool stays silent.

4.1. Aerial Reconnaissance of Electric Poles in the Power Grid for Maintenance and Surveillance Purposes

Ensuring the continuous reliability and performance of power transmission and distribution networks requires effective maintenance. However, maintaining these extensive grids with numerous interconnected components spread across long distances presents a complex challenge. Environmental conditions such as wind, rain, extreme weather events and wear further contribute to the complexity. For example, the Italian energy grid spans over 74,000 km, including high-voltage lines and transformer stations.

Mapping and surveying electric poles in the grid are time-consuming tasks. Automation is seen as a promising strategy to handle the thousands of poles involved. Visual inspections are conducted through aerial flights [51,52] or remote sensing images [53] to identify relevant issues. Accurately identifying individual poles from aerial images poses challenges due to variations in angles and operating conditions. Reidentifying the same object, such as poles, from different images requires algorithms that can automatically accomplish this task [54]. Siamese networks, commonly used for object reidentification, process different images using the same architecture. These networks are trained to ensure that embeddings of the same object are closer than those of different objects [55]. However, relying solely on raw visual images for reidentification is insufficient when the object of interest occupies a small portion of the image and overlaps significantly with the background.

In a recent study by Devoto et al. [56], a deep learning-based strategy for reidentifying objects in aerial reconnaissance missions is proposed. This strategy is crucial for maintaining and monitoring critical infrastructures. The authors utilize a domain-specific object detector to extract assets associated with the detected objects and employ a Siamese neural network for reidentification. The network uses both visual features and graphs to describe asset relationships. The effectiveness of this approach is demonstrated in reidentifying electric poles in the Italian energy grid. Inspired by graph deep learning [55,57] and object-centric models [58,59], the authors train a customized object detection model and construct a graph based on the extracted assets. The Siamese neural network is trained on two distinct embeddings—one in the original image domain and the other in the graph domain—to identify poles based on both asset appearance and relationships. To construct the embedding based on graphs, the authors utilize graph neural networks (GNNs), which are a type of neural networks capable of maintaining permutation-equivariance to objects present in the image [55]. GNNs can process a mix of features including object detection features, position features that can be trained [60] and relational features without excessive repetition. The proposed approach outperforms standard reidentification methods that rely solely on visual features. The authors suggest that these hybrid approaches incorporating graphs could become integral in the next generation of AI algorithms for predictive maintenance and anomaly detection in power grids.

Subsequent efforts will revolve around expanding this framework to additional scenarios, assessing the interpretability of the pipeline, examining the object detection model's resilience and refining the methods used to construct the asset graph.

4.2. Robust Anomaly Detection in Photovoltaic Production Plants

Various applications have focused on predictive maintenance and anomaly detection in the operations of photovoltaic plants [61–63]. Enel Green Power, in particular, aimed to develop an AI application for the 3SUN Factory's sun cell production line, with a specific focus on predicting faults in the ventilation fans of the automatic wet bench (AWB) machine. Data from the manufacturing execution system (MES) were collected and used in the predictive analytics engine for fault prediction.

In this regard, Arena et al. in [64] conducted a study on anomaly detection in the 3SUN solar cell production plant in Catania, Italy. They explored a Monte Carlo-based preprocessing technique as an alternative to commonly used methods. Monte Carlo simulation is commonly used as a preprocessing technique to effectively manage uncertainty in experimental manufacturing and energy management situations, particularly in predictive maintenance [65–68] or predictive analytics uses [69]. The proposed method from [64] offers advantages such as replacing outliers and preserving temporal locality in relation to the training dataset. Following preprocessing, the authors trained an anomaly detection model using principal component analysis and defined appropriate key performance indicators for each sensor in the production line. By monitoring these indicators and setting predefined thresholds, anomalous conditions can be isolated, triggering alarms when necessary. The approach was successfully tested under normal and anomalous scenarios, demonstrating its ability to anticipate equipment faults and handle false alarms.

To evaluate the effectiveness of the predictive model, the authors of [64] calculated the average downtime for the AWB stage and estimated the reduction in downtime resulting from the adoption of the model. Considering that only a portion (amounting at most to 50%) of predicted machine downtime events can be completely avoided due to preventive maintenance limitations, a significant reduction in AWB downtime was observed, leading to an increase in annual photovoltaic panel production by approximately 1–2 MW.

Future work should involve testing the proposed methods on multiple pieces of equipment to further validate their scalability.

4.3. Anomaly Detection in Horizontal Axis Wind Turbines

Wind power is a rapidly growing form of renewable energy and plays a significant role in decarbonization efforts. However, wind turbines are vulnerable to various dynamic loads, resulting in frequent failures and downtime periods.

In addition to capital expenditure (CAPEX) investments, operation and maintenance (O&M) costs are substantial. The electric and control systems are the most common areas of faults, followed by blades and hydraulic groups [70,71]. Failures typically occur in generators and gearboxes, leading to high repair and replacement expenses and causing significant production losses due to extended periods of downtime. To address these

O&M challenges, remedial approaches focus on implementing condition monitoring (CM) strategies capable of early fault detection and isolation.

CM typically involves acquiring high-frequency data, such as vibrational analysis, which can be processed using various methods (refer to [72] for a recent review). The latest generation of multi-megawatt (MW) wind turbines [73–75] integrates sensor networks within supervisory control and data acquisition (SCADA) systems to monitor the powertrain status. This includes variables such as bearing temperature and lube oil sub-system, with the standard practice of recording 10-min averaged values and other statistical parameters from the sensor time series. Operators face the challenge of identifying fault signatures within the data streams and distinguishing them from other behavioral factors. This task is demanding due to the heterogeneity of signals and the loss of high-frequency temporal dependencies caused by the 10-min averaging process.

In [76], Miele et al. proposed an innovative unsupervised deep anomaly detection framework to identify anomalies in horizontal axis wind turbines using SCADA data. Their approach simultaneously considers the information content of individual sensor measurements (graph node features) and the nonlinear correlations among all pairs of sensors (graph edges). They introduced a graph convolutional autoencoder designed specifically for multivariate time series, treating the sensor network as a dynamical functional graph. This structure leverages the unsupervised learning capabilities of autoencoders by incorporating both individual sensor measurements and the nonlinear correlations between signals. The framework was validated using data collected over 20 months from four wind turbines, during which 12 failure events occurred.

The proposed neural architecture is trained to learn the normal behavior of the system without relying on labeled data. Based on the model's reconstruction errors, multiple monitoring indicators are defined, including a global Mahalanobis indicator for the entire sensor network and a local residual indicator for each monitored variable. These indicators are evaluated considering both their magnitude and duration using a four-stage threshold method.

Once the four-stage threshold is applied, a warning is triggered for the sensor with the highest reconstruction error. The proposed method was validated using 10-min SCADA data from four wind turbines within the same wind farm, each with a rated power of 2 MW.

The dataset consisted of 12 failures in critical components (generator, gearbox and transformer) that were observed over a 20-month operation period. The model presented in the study was compared to two other approaches that used long short-term memory neural networks. The presented model exhibited superior performance, achieving 100% precision and a 91% F1-score. It successfully detects hidden anomalies, even when the turbine continues to deliver the requested power to the grid.

4.4. Data-Driven Estimation of Current and Ampacity on High-Voltage Overhead Lines

The Italian electricity grid has undergone a significant transformation due to the rapid growth of renewable energy sources such as wind, photovoltaic and hydroelectric power generation. This shift has influenced the development of the electricity production sector in Italy and Europe over the past decade. Users now have a dual role as consumers and producers, actively participating in energy exchange and functioning as integral nodes within the network. To achieve national decarbonization goals, embracing digitalization and innovative grid solutions is crucial. This involves integrating electrical infrastructures with cutting-edge digital tools installed on pylons and leveraging Industrial Internet of Things (IoT) technologies.

Dynamic thermal line rating (DTLR) systems are used to evaluate transmission line capacities and can be classified into indirect and direct methods. Indirect methods gather data related to weather conditions [77,78], while direct methods measure parameters such as conductor sag, ground clearance, line tension and conductor temperature [79–86]. Real-time line monitoring devices for overhead transmission lines, including those in renewable energy installations, are discussed in [87–89]. Reference [90] proposes an optimal algorithm aiming at managing real-time congestion in the overall electric transmission system, considering quasi-dynamic thermal rates of transmission lines. Commercially available DTLR systems are explored in [91,92], showcasing their application to a real-world 220 kV connection. Furthermore, Ref. [93] presents a Terna-sponsored study that proposes a dynamic thermo-mechanical model approach using weather data collected by IoT sensors to estimate conductor temperature and power grid ampacity accurately.

DTLR systems and georeferencing of the electrical system represent significant advancements for high voltage networks, leading to intelligent cyber-physical systems. Continuous monitoring of crucial parameters such as conductor temperature and voltage allows for greater flexibility in overhead power line ratings. The model presented in [93] demonstrates high reliability in estimating line temperature and ampacity by focusing on the thermal limit of conductor materials and their technical catalog ampacity values. The authors also suggest incorporating machine learning algorithms to reduce computational complexity and enable line temperature forecasting. Future work could enhance the proposed model by including data on the conductor distance from the ground, thus achieving even more precise evaluations of current ampacity.

4.5. AI for Learning the Behavioural Profiles of Power Consumers as Relevant Insight for Estimating Power Demand in Distribution Networks

The need to safeguard the environment has spurred the energy transition towards understanding consumers' habits and accurately profiling them. These processes can lead to significant reductions in consumption and optimizing resources, and aligning energy production with actual demand [94].

To effectively manage renewable energy generation and distribution, grid operators consider it crucial to profile end-users based on data from the Internet of Energy [95]. Energy companies typically assign a load curve to consumers for energy distribution and billing purposes, based on the energy consumption model relevant to the consumer's economic sector (e.g., agriculture, manufacturing, transportation) [96,97]. However, these energy profiling approaches fail to consider changes in consumer habits and electricity usage. Moreover, the initially assigned load curve may be incorrect due to different electricity usage patterns compared to the typical consumer group [97]. Load profiles within the same business category often exhibit diverse electricity consumption habits, making the use of business sectors for consumer categorization inefficient [96]. To address this, various energy profiling techniques have been proposed that consider a consumer's energy consumption over a period. These techniques enable the provision of personalized energy services based on consumer profiles [98].

With the rise of Industry 4.0, smart meters can measure energy consumption remotely multiple times per day, generating detailed data on building energy consumption at various levels. This facilitates a more accurate identification of consumer habits [99]. Machine learning algorithms play a crucial role in extracting useful information from smart monitoring data, allowing a deeper understanding of consumer habits and dynamics. Unsupervised learning techniques, particularly clustering methods, are particularly useful for data mining and machine learning. Clustering involves grouping objects with similar observed patterns into different clusters [100].

Energy profiling models mainly rely on partitional approaches such as K-means [96,98,101,102], hierarchical approaches [97,103] and shape-based models such as K-shape [99]. These models are often combined with deep learning techniques such as autoencoders and self-organizing maps [100,101]. However, traditional clustering algorithms have limitations. They struggle to capture temporal dynamics and sequential relationships within data [104,105]. Conventional clustering techniques use distance functions to identify clusters of predefined shapes, focusing only on local relationships among neighboring data samples and disregarding long-distance global relationships [106].

In [107], the authors propose a clustering approach that combines a specific algorithm based on dynamic time warping (DTW) clustering with complex network analysis (CNA) to identify typical behaviors and similarities in energy load profiles. This approach combines the effectiveness of DTW in capturing similarities among time series [63] with the ability of CNA to reveal correlations or similarities among individuals within a network [108–110].

According to [107], utilizing an algorithm that leverages a specific distance metric for time series, such as DTW, enhances the accuracy of clustering different energy profiles. This addresses most of the limitations of previous models in the literature that struggle to capture temporal dynamics and sequential relationships within time series. The effectiveness of the methodology was demonstrated using a real dataset of historical consumption data from 100 commercial and industrial consumers over a one-year period. The authors successfully identified the main characteristics of consumers by tracking their behavior through identifying primary patterns of daily energy consumption and periods of higher consumption throughout the year. Additionally, by incorporating CNA, consumers with similar behaviors were grouped together regardless of their macro category. Combining this profile identification methodology with forecasting techniques allows suppliers to predict each consumer's energy consumption and generate the required amount of energy for each consumer.

For the sake of completeness, we point out that stochastic methods too can be applied to forecast the load curve assigned to a consumer. Stochastic methods are useful for capturing the inherent uncertainty and randomness in energy consumption patterns. They can provide probabilistic forecasts that not only estimate the expected load, but also provide information about the range of possible outcomes.

Even if they are less practiced than the methodologies mentioned above, we report below a few examples of stochastic methods that can be used for load curve forecasting, as discussed in [111,112]:

- ARIMA (autoregressive integrated moving average) models are widely used in time series forecasting. They capture the dependencies and trends in historical load data and use them to make future predictions, handling both deterministic and stochastic components in the data, thus making them suitable for load curve forecasting.
- SARIMA (seasonal autoregressive integrated moving average) models extend the capabilities of ARIMA models by incorporating seasonal patterns in the data. Load curves often exhibit seasonal variations, such as daily or weekly patterns. SARIMA models can effectively capture and forecast these seasonal fluctuations.
- Gaussian processes are flexible and non-parametric models that can capture patterns in data. They are particularly suitable when the underlying relationships between variables are nonlinear. They have been successfully applied to load curve forecasting by modeling the load curve as a function of time and capturing the uncertainty through the covariance structure.
- BSTS (Bayesian structure time series) models are Bayesian state-space models that can capture both trend and seasonality in the data. These models decompose the load curve into multiple components, such as level, trend, seasonality and noise, allowing for a more comprehensive analysis. The Bayesian framework also enables the incorporation of prior knowledge and updating of forecasts as new data becomes available.
- Finally, LSTM (long short-term memory) networks are a type of recurrent neural network that can effectively model sequential data. They have shown promise in load curve forecasting by capturing long-term dependencies and temporal patterns in the data, due to their flexible architecture, allowing for modeling complex relationships within the load curve data.

For the sake of clarity and readability, in Table 4 we recap the references cited in Section 4, distinguishing between challenge faced and the methodological approach chosen to tackle each challenge.

Table 4. Literature review relative to predictive maintenance and anomaly detection in energy management.

Challenge Faced	Methodological Approach	Reference
Pole mapping on overhead power lines	Mapping out all the poles of the networks with cyclically planned aerial flights	[51]
Pole mapping on the generic power grid	Mapping out all the poles of the networks with cyclically planned aerial flights	[52]
Power line corridor surveys	Algorithm for automatic reidentification of the same object from different pictures	[53]
Mission of aerial reconnaissance for the reidentification of electric poles in the Italian power grid	Deep learning-based strategy for reidentifying the same object in different photos taken from separate positions and angles	[56]
Predictive maintenance for photovoltaic power plants	Data-driven toolkit	[62]
Predictive maintenance for photovoltaic power plants	Data-driven approach based on sensor network analysis for unveiling hidden precursors in failure modes	[63]
Anomaly detection for the 3SUN solar cell production plant in Catania, Italy	Robust anomaly detection using Monte Carlo-based pre-processing	[64]
Fault detection for wind turbines from SCADA data	Clustering algorithms and principal component analysis combined with anomaly detection to capture fault signatures	[70]
Wind turbine reliability data review	LCOE estimation using reliability data	[71]
Fault indicator synthesis and wind turbine monitoring using SCADA data	Combined mono- and multi-turbine method for fault indicator synthesis	[73]
Early fault detection in wind turbines	Exploitation of CNNs for enhancing detection accuracy and robustness	[75]
Anomaly detection in horizontal axis wind turbines	Unsupervised deep anomaly detection based on SCADA data	[76]
Estimation of dynamic thermal capacity of overhead transmission lines	Direct methods for DTLR	[80]
Real-time monitoring of overhead transmission lines	Prototype for real-time transmission line monitoring via direct methods	[82]
Voltage and ampacity monitoring for overhead lines	Real-time monitoring system based on conductor tension, ambient temperature, solar radiation and current intensity	[83]
Predictive maintenance in power transmission networks	Real-time monitoring	[84]
Dynamic thermal rating on overhead transmission lines	Design, installation and field experience	[85]
Dynamic thermal rating on overhead transmission lines	Temperature measurement via surface acoustic wave sensors	[86]
Dynamic line rating on overhead lines	Real-time monitoring	[87]
Dynamic line rating on overhead lines	Line current variation model for representing the forecasting error of intermittent renewable energy sources, with the aim of preventive control	[89]
Real time congestion management in power systems	Quasi-dynamic thermal rating considering congestion clearing time	[90]
Predictive maintenance on the case study of the Sicilian power network in Italy	Optimization of generation from renewable energy	[92]
DTLR for current and ampacity estimation on high-voltage overhead lines	Dynamic thermo-mechanical model using weather data measured by IoT sensors to properly estimate conductor's temperature and ampacities of power grids	[93]

Table 4. *Cont.*

Challenge Faced	Methodological Approach	Reference
Characterization of the medium-voltage loads	Data-mining based methodology	[95]
Learning the behavioural profiles of power consumption in a smart grid	Data-driven method based on hourly measured electricity used data from a large number of customers	[96]
Learning the behavioural profiles of power consumption in a smart grid	Multi-layered clustering	[97]
Detection of building energy usage patterns	K-shape clustering algorithms	[98]
Profiling energy consumption in buildings	Adaptive self-organizing map for clustering	[99]
Profiling residential electricity demand	K-means clustering	[100]
Learning the behavioural profiles of power consumption in a smart grid	TPL (typical load profile) data-driven generation	[102]
Learning the behavioural profiles of power consumption in a smart grid	Feature selection in multi-sensor data for time series clustering	[104]
Learning the behavioural profiles of power consumption in a smart grid	Community detection in complex networks for time series clustering	[105]
Learning the behavioural profiles of power consumers as relevant insight for estimating power demand in distribution networks	Profiling algorithm based on DTW combined with CNA	[106]
Analysis of photovoltaic power plant operations and failure modes	Data-driven approach based on graph modeling techniques	[63]
Load balancing in smart grids	Wardrop control algorithm	[110]

5. Discussion

The overall aim of the paper is to critically review the relevant energy network scenarios where applied control and AI are expected to yield significant benefits.

In Section 2, we targeted the problem of cost-effective charging of electric vehicles in service areas, even in the presence of renewable energy sources and energy storage units.

The high power levels required by fast charging are necessary for yielding acceptable recharging times for the drivers. This means that just a few fast-charging sessions at the same time may cause power flows at the POC of the service area with the distribution grid to rise to several tens or hundreds of kilowatts, which implies high costs for operating the service area. For this reason, the introduction of ESS technology would allow to mitigate the effort for the grid since it would contribute to the peak power requests from PEVs, reducing the power flow at the POC as a result. A similar effect in terms of power peak mitigation at the POC is produced by resorting to renewable power generators as a further source of clean energy for recharging PEVs. Moreover, another relevant control requirement is to be able to cope with the uncertainty that is intrinsic, on the one hand, to the PEV power demand—as this depends on the arrival times and charging requests of the single vehicles—and, on the other hand, to renewable power generators.

In this respect, stochastic MPC, as proposed in [17], is currently the most promising approach, allowing for the extension of the formulation with the modelisation of ESS power losses and with control flexibility on the power set point of recharging sessions. At the same time, in order not to negatively affect the drivers' charging experience, the proposed controller is constrained to track as much as possible the exact amount of power that the PEVs request by pursuing the objective of minimum charging time. Future work is being aimed at introducing further constraints and uncertainty variables in the formalization in order for the experimental setup to reproduce the real-world scenario as much as possible.

In Section 3, we reviewed the recent literature targeting the problem of cyber-physical system security, with specific reference to defense schemes against LAAs in power transmission networks.

Among many efforts at devising defense schemes against such attacks, the authors of [39,40] propose a robust control strategy that pursues optimal ESS placement in order to protect the power transmission network against a whole set of identified potential dynamic LAAs. As ESSs are becoming an integral part of modern power networks, the flexibility offered by their ability to absorb or release power in a controlled way enables the provision of ancillary services for improving power quality and voltage stability. Applied control is therefore expected to help protect power transmission grids from cyber-physical attacks aimed at tampering electrical loads, and, in this case too, future work will be aimed at introducing and satisfying further boundary conditions in the problem formalization and control-theoretic solution, so that the experimental setup eventually proves to be as realistic as possible and reproduces the most frequently used network topologies.

Section 4 is devoted in general to reviewing the recent literature on predictive maintenance and anomaly detection in energy management. More in detail, we provided a literature review of the following specific topics: aerial reconnaissance of electric poles in the power grid for maintenance and surveillance purposes, robust anomaly detection in photovoltaic production plants, anomaly detection in horizontal axis wind turbines, data-driven estimation of current and ampacity on overhead lines and, last but not least, AI for learning the behavioural profiles of power consumers as relevant insight for estimating power demand in distribution networks.

AI-driven algorithms have indeed proven to be key for optimally selecting the location for planning the installation of a power plant; additionally, AI-driven anomaly detection has proven to be effective at predictive maintenance in power plants and at enabling intelligent aerial reconnaissance of high-voltage overhead power lines, especially with the help of computer vision software on drones and helicopters. Computer vision, in particular, has turned out to be helpful for performing industrial safety tasks in power plants in order to minimize the risk of injury for human operators. AI offers the possibility to estimate in real-time the conditions of power lines, enabling predictive maintenance to effectively contrast potentially disruptive atmospheric phenomena such as the layers of ice that, by progressively accumulating, threaten to sink or break line connections. Future work in this respect may be aimed at augmenting the proposed models with more available data sources in order increase task accuracy and robustness, as well as at extending the proposed framework to other use cases, also with the help of graph-theoretic techniques.

6. Conclusions

The paper provides an extensive literature review specifically limited to recent trends in applied control and AI for EV charging, cyber-physical security and predictive maintenance, as these were identified during the 2023 States General of AI event [1] to be the contexts which most of the business needs of energy companies currently revolve around.

Applied control is definitely expected to help cost-effective fast charging of EVs in service areas, as well as to protect power transmission grids from cyber-physical attacks aimed at tampering electrical loads. In this respect, future work will be aimed at introducing further constraints and uncertainty variables in the formalization in order for the experimental setup to reproduce the real-world scenario as much as possible.

Relative to predictive maintenance and anomaly detection in energy networks, the paper provides a literature review of the following specific topics: aerial reconnaissance of electric poles in the power grid for maintenance and surveillance purposes, robust anomaly detection in photovoltaic production plants, anomaly detection in horizontal axis wind turbines, data-driven estimation of current and ampacity on overhead lines, and, last but not least, AI for learning the behavioural profiles of power consumers as relevant insight for estimating power demand in distribution networks.

All in all, the possibility, with applied control and AI, to design and operate digital twins of energy networks and power plants is expected to be a game changer in terms of intelligent management of assets, at the generation, transmission, distribution and consumption level.

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