Review

A Review of Edge Computing Technology and Its Applications in Power Systems

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Abstract: Recent advancements in network-connected devices have led to a rapid increase in the deployment of smart devices and enhanced grid connectivity, resulting in a surge in data generation and expanded deployment to the edge of systems. Classic cloud computing infrastructures are increasingly challenged by the demands for large bandwidth, low latency, fast response speed, and strong security. Therefore, edge computing has emerged as a critical technology to address these challenges, gaining widespread adoption across various sectors. This paper introduces the advent and capabilities of edge computing, reviews its state-of-the-art architectural advancements, and explores its communication techniques. A comprehensive analysis of edge computing technologies is also presented. Furthermore, this paper highlights the transformative role of edge computing in various areas, particularly emphasizing its role in power systems. It summarizes edge computing applications in power systems that are oriented from the architectures, such as power system monitoring, smart meter management, data collection and analysis, resource management, etc. Additionally, the paper discusses the future opportunities of edge computing in enhancing power system applications.

Keywords: cloud computing; edge computing; power system; distributed energy resources; grid edge; smart grid

1. Introduction

Edge computing is a transformative approach in the field of distributed computing, designed to bring data processing closer to the data source, such as sensors, Internet of Things (IoT) devices, or local servers. It emerged from the increasing demand for real-time data processing capabilities, as it minimizes the need for data transmission over long distances. To fully understand the role of edge computing, it is essential to address its relationship with cloud computing.

Cloud computing has been one of the most popular topics in the information technology area over the past decades. In October 2007, IBM and Google announced a collaboration in cloud computing [1,2], which marked a significant milestone. Since then, cloud computing has been widely discussed and used. Typically, the cloud computing paradigm is based on transmission control protocol (TCP)/internet protocol (IP) and involves the high integration of configurable computing resources [3]. It encompasses data storage, management software, data transmission network, cloud center, and related applications. Cloud computing operates as a computational paradigm that collects data from the end devices and sends it to a centralized cloud server for further processing and computation. It boasts advanced characteristics such as being service-oriented, loosely coupled, and strongly fault-tolerant [1]. Cloud servers usually possess supercomputing power capable of handling various large-scale computing tasks.

Conventionally, cloud computing is implemented using three cloud computing services: Software-as-a-service (SaaS) is responsible for running, managing, and maintaining

the applications and the infrastructure on which the applications run; Platform-as-a-service (PaaS) provides customers with cloud resources such as hardware to develop, run and manage consumer-created applications without building and maintaining these resources; Infrastructure-as-service(IaaS) delivers computing, storage, virtual machines, and other fundamental resources to consumers.

With the development of network-connected intelligent devices and the growing needs of end users, intelligence has become integrated into various aspects of the industry and people's daily lives [4]. The significantly increasing number of smart edge devices has led to a larger data scale. According to Cisco's statistics, there were 17.1 billion devices on the Internet in 2016 [5]. The Cisco Annual Internet Report (2018–2023) White Paper published in 2020 [6] indicated that there were 18.4 billion devices connected to the Internet, projected to rise to 29.3 billion by the end of 2023. Dell Technologies also predicts that there will be 41.6 billion IoT devices in 2025, producing 79.4 zettabytes (ZB) of data [7]. These statistics highlight the growing data scales and increasing complexity of data processing tasks. The limitations of cloud-based architectures are becoming evident. Firstly, intelligent devices are often used for real-time data processing. For example, an IoT-enabled intelligent automobile [8] generates a significant amount of data [9], necessitating servers to receive and handle the data. The response speed of these servers is critical. Secondly, end devices are often placed across a wide range of geographical locations. The failure of some end devices and the long transmission distance increase resource consumption. Thirdly, ensuring the security of end devices' data is another significant concern. Typically, cloud centers collect and store vast amounts of user personal data, including private information. Information leakage can lead to unacceptable consequences.

To address these challenges, an alternative solution that can process the massive data instantly, efficiently, and safely is necessary. Consequently, edge computing has emerged and gained popularity in recent years. It represents a variant of distributed computing architecture designed to process data at the grid edge with the end devices [10]. Instead of transmitting data from each device at the edge of the network to the cloud center, the edge computing architecture enables the edge servers to collect, process, and store the data locally. By allowing data to be collected, processed, and stored on local edge servers, both the response speed and the safety of sensitive data can be improved. Furthermore, the management of the end devices across various geographical locations can rely on these local edge servers, helping eliminate the vision gaps between cloud servers and local edge devices.

As shown in Figure 1, the edge computing architecture comprises three tiers: central tier, edge tier, and device tier [11]. The central tier aims to provide wide connectivity coverage using cloud computing services, where vast computational resources and storage capabilities are employed to process and manage large-scale data tasks. The edge tier serves as an intermediary layer that extends cloud capabilities closer to the data source by deploying edge servers between the cloud and end devices to handle intermediate data processing, reducing latency and bandwidth usage while still leveraging cloud resources for more intensive tasks. Edge computing further pushes data processing to the very edge of the network, right at or near the data sources. The device tier consists of various end devices with limited computing and storage resources, such as sensors and actuators, responsible for collecting raw data. The edge server layer receives raw data from the local end devices nearby and pre-processes the data. Subsequently, the pre-processed data is sent to the edge computing layer or cloud server for further processing and computing. As interconnected layers, cloud computing and edge computing collectively enhance the efficiency and effectiveness of data processing in today's digital infrastructures. The proximity reduces latency, conserves bandwidth [12], enhances security, reduces energy consumption of cloud centers, and improves the responsiveness of applications.

Edge computing communication can be categorized into two layers: (i) access networks, which connect the device tier with the edge tier, and (ii) transport networks, which connect the edge tier with the central tier.
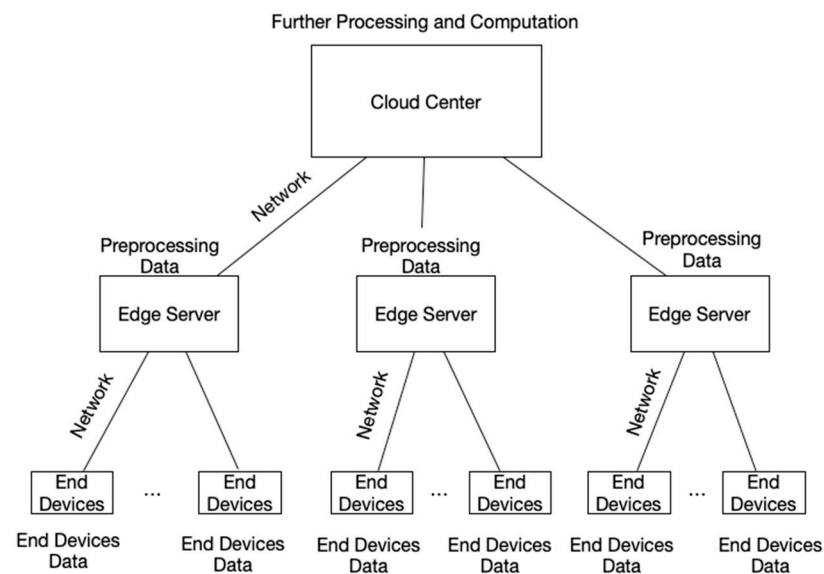
Further Processing and Computation

Cloud Center

Preprocessing Data

Edge Server

Network

End Devices ... End Devices

End Devices Data

Figure 1. Workflow diagram for the general edge computing architecture.

In edge computing systems, communications are frequently between access points and end devices. The edge servers typically perform as small data centers that are co-located with the wireless access points. For example, the edge servers can be placed in the local base stations to eliminate the additional expenditure. Access points are also responsible for accessing large-scale cloud data centers. Different access technologies, including cellular wireless networks and fiber-wireless access networks, can be used to connect edge devices and edge servers. When edge devices are positioned at the wireless access point, they can directly access edge servers through the radio channels. In such scenarios, cooperative communication abilities of wireless channels can optimize task offloading through relaying via nearer mobile devices.

In recent years, the 5th generation mobile network (5G) has emerged as a cellular network technology capable of providing higher-quality communication and improving the quality of service. This feature enables 5G to support highly interactive applications with high throughput and low latency [13]. Edge computing can benefit from 5G by bringing computing resources from the cloud to the end users. Compared with the traditional cloud computing model, edge computing in 5G is more suitable for highly computational and interactive applications.

Edge computing has been successfully applied in various areas. Recently, the increasing need for renewable energy integration and decarbonization has led to a rapid expansion in the deployment of distributed energy resources (DERs) and sensors. Power systems have become one of the areas that benefit significantly from edge computing.

Power systems are complex, hierarchical physical networks that generate, transmit, and distribute electricity to consumers, carrying massive amounts of information. Wide-area coordinated management and control among generation, transmission, load, and distribution is crucial to ensure reliable power system operations [14]. Cloud computing is a paradigm that can provide end users with various services by integrating various virtualization technologies on the cloud side. This mechanism enables the operators and end users to access abundant computing resources and data storage capacities via the network without purchasing and maintaining hardware. In the past few decades, cloud computing has been increasingly used in power system analysis and control. For example, in 2014, Mercury Energy used cloud computing to provide services to help customers manage their power consumption [15]. Measurements collected from multi-sources at substations are sent to the cloud centers for future processing and analysis. With the development of smart grids, an increasing number of network-connected devices are integrated into power systems, leading to an exponential increase in data loads. Effectively managing and

processing the massive data generated by these widely distributed devices is a critical challenge, especially for traditional centralized approaches that require real-time processing. Compared with cloud computing, edge computing can offer a decentralized paradigm that allows the smart devices to process the data at the edge of the network by themselves. Furthermore, the raw data collected by end devices can be stored and pre-processed in the small data centers at the network edge instead of sending to the centralized center. These features enable real-time monitoring and control of these devices, support advanced metering infrastructure (AMI), and aid in predictive maintenance. Edge computing can also benefit enterprises by increasing the reliability of the power supply systems.

This paper aims to provide a comprehensive review of the state-of-the-art edge computing technology for power system engineers who may not be very familiar with the fundamental science of edge computing yet but are interested in understanding its capabilities, architectures, and existing and potential applications in a variety of domain areas, particularly power systems. The main contributions of this paper include the following:

- A review of generalized edge computing architectures and their applications;
- A review of popular edge computing technologies;
- A review of edge computing applications in power systems that are oriented from the architectures;
- A discussion of future opportunities of edge computing in power systems.

The rest of the paper is organized as follows: Section 2 presents the state-of-the-art of edge computing architecture; Section 3 reviews the main technologies and relative works of edge computing in general areas; Section 4 reviews the existing applications of edge computing in power systems; Section 5 discusses the works in this paper and future opportunities for edge computing applications in power systems; Section 6 concludes the paper.

2. Review of Edge Computing Architectures

In this section, we will present various edge computing architectures (e.g., multi-access edge computing (MAEC), cloudlet computing, and fog computing) and their applications in multiple domain areas.

2.1. Multi-Access Edge Computing (MAEC)

MAEC, previously known as mobile edge computing (MEC), was defined by the European Telecommunication Standards Institute (ETSI) as applying the concepts of cloud computing on the information technology (IT) based servers at the network edge [16]. MEC can be generally described as a cloud server capable of running at the edge of a mobile network, handling tasks beyond the scope of traditional network infrastructure [16]. While specific designs of MEC vary, the basic idea of MEC can be outlined with the five major characteristics defined by ETSI: on-premises means the edge side is local and may operate separately from the rest of the network while still accessing local resources; proximity, MEC servers are positioned close to the data source, and may have direct access to devices; low latency, due to their proximity to devices, MEC can significantly reduce latency; location awareness, as part of a wireless network, local edge servers can detect the location of connected end devices by leveraging lower-level signaling information; network context information, applications and services can leverage real-time network information to provide context-related services [17].

In September 2017, the ETSI Industry Specification Group (ISG) officially changed its name from MEC to MAEC. The change reflects that the edge is not only based on mobile networks. The ISG has defined the framework and the reference architecture for MAEC. Figure 2, a simplified version of the MAEC framework from Chapter 5 of [18], illustrates the general entities involved. These entities are categorized into system level, host level, and network level [18]. The network level comprises relative external network entities, such as the 3rd generation partnership project (3GPP) network, local network, and external network. The MAEC host level involves the MAEC host and corresponding management

entities. The MAEC host can be viewed as the combination of the MAEC platform, MAEC applications, and virtualization infrastructure. The MAEC system level is at the top of this framework, with overall management having an encompassing view of the entire MAEC system.
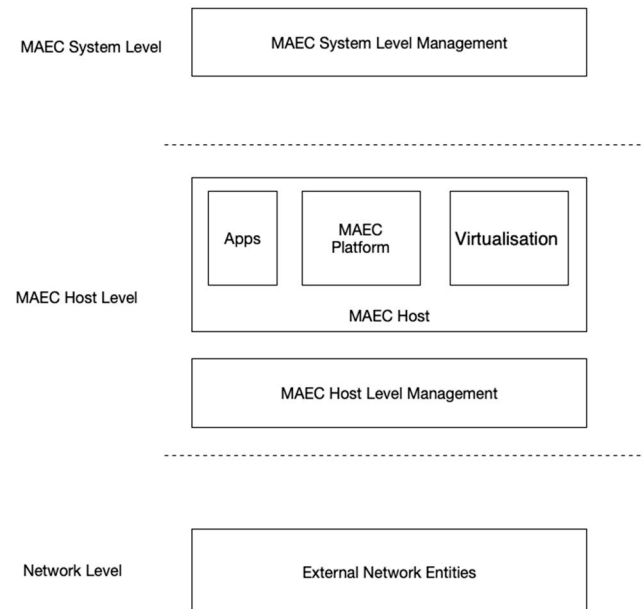

Figure 2. Multi-access edge computing framework.

The ISG also provided an MAEC reference architecture, which offers more details about the functional entities and their interrelations [19]. Figure 3 illustrates a simplified version of the framework from Chapter 6 of [18]. The MAEC host comprises the MAEC platform and the virtualization infrastructure, responsible for computing, data storage, and network resource management. The MAEC platform encompasses several essential functions necessary for running MAEC applications. The MAEC platform manager and the virtualization infrastructure manager operate at the MAEC host level. They provide management of specific MAEC hosts and their applications. At the MAEC system level, the MAEC orchestrator has comprehensive oversight of the entire MAEC system.
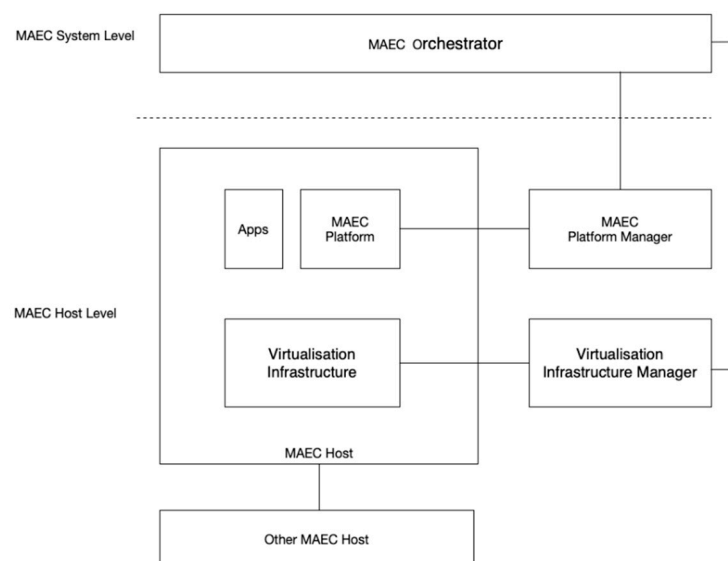

Figure 3. Multi-access edge system reference architecture.

Numerous applications benefit from the emergence of MAEC.

2.1.1. Healthcare

MAEC plays a critical role in the healthcare domain. For example, sensors can be attached to individuals affected by disasters. The signals and information can be transmitted to the nearby edge server for future analysis, aiding rescuers in assessing the overall situation [20]. In [21], the authors presented a three-level architecture for a smart health system. This system integrates a role model, layered-cloud architecture, and an MAEC paradigm that allows caregivers to collect the information regardless of their patient's geographical location.

2.1.2. Smart City

Smart cities are in high demand nowadays. Sneppe et al. proposed using MAEC to transfer data in smart cities [22]. Mobile devices have become one of the primary data sources. An edge server near the mobile terminal can rapidly receive and store data. Sapienza et al. [23] presented a scenario that involves MAEC for detecting abnormal or suspicious events such as terrorist threats and natural disasters. The MAEC architecture enables cooperation among the Base Transceiver Stations. Experimental results demonstrate that this system can notify users in high-risk areas promptly.

2.1.3. Video Analytics

Surveillance cameras typically follow the client–server architecture. The cameras stream the data to the servers and await processing. As the number of surveillance cameras grows and image quality improves, the traditional architecture might not be able to handle the significant amount of data. MAEC can address this by implementing lightweight programs on end devices. Furthermore, the application can also be used for face recognition [24,25].

2.1.4. Connected Vehicles

Intelligent connected vehicles can communicate with each other on the road through the network. Leveraging the MAEC environment along the road can integrate the intelligent vehicles and enable two-way communication between them. One vehicle can share information with surrounding vehicles. Additionally, MAEC can enable scalable, reliable, and distributed environments synchronized with local sensors [26].

2.2. Cloudlet Computing

Satyanarayanan et al. first proposed the concept of the Cloudlet [27]. They defined the Cloudlet as a trusted computer or cluster of computers that have rich resources. These computers or clusters of computers connect to the Internet well and are available for use by nearby mobile devices. In this way, we can obtain real-time responses. Cloudlets are generally located in one-hop proximity to mobile devices. Access to the Cloudlet usually has low latency and high bandwidth. Furthermore, virtual–machine techniques allow the Cloudlet to operate in disconnected mode [28].

Figure 4 represents the general architecture of Cloudlet computing. This architecture shows that mobile devices connect to nearby Cloudlet servers to transmit data [29,30]. The Cloudlet server receives the job from the mobile devices, identifies the user's cloud service provider, and sends back the end user's environment [30]. The cloud server provider also waits for the Cloudlet to make contact. Once the connection between the end user and the Cloudlet is established, the cloud service provider retrieves the user's environment.

Several applications based on the Cloudlet computing architecture are listed as follows.
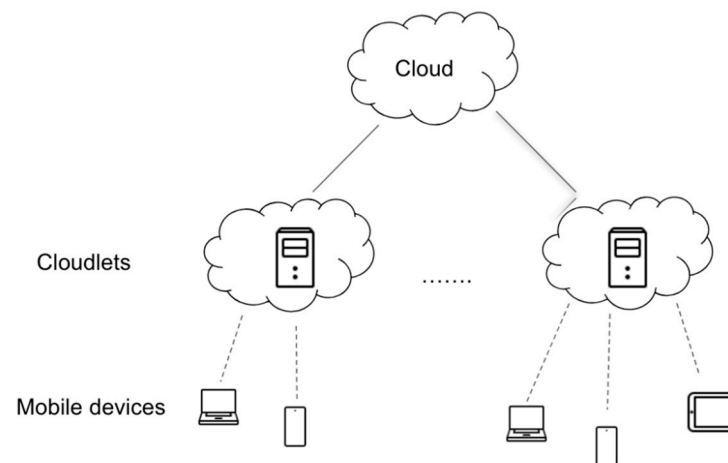
Figure 4. The overall hierarchical architecture of Cloudlet computing.

2.2.1. Face Recognition

Soyata et al. [31] used a mobile–Cloudlet–cloud architecture to develop a face recognition system. They demonstrated that the power of Cloudlet servers can reduce the overall response time of face detection compared to prior work.

2.2.2. Healthcare

Chandavale et al. [32] developed a Collaborative Intrusion Detection System based on Cloudlet computing. They believed that the mobile–Cloudlet–cloud architecture minimizes communication time, benefiting patients.

2.2.3. Smart Homes

A Cloudlet computing approach is used in Wireless Fidelity (Wi-Fi) positioning and navigation in [33]. The authors proposed a Cloudlet computing system that provides accurate position and navigation on a one-hop wireless network. The self-driving indoor cart can make real-time interactions with the accurate point data collected by this system.

In [34], the authors proposed a delay-aware Cloudlet placement strategy with an enhanced k-means algorithm. This technique enabled a mobility-enhanced environment and calculated the optimal Cloudlet position. The proposed strategy can improve the service quality of healthcare support by minimizing the network access delay between sensors and Cloudlets.

Hughes et al. [35] implemented a floor-based walk detection system with Cloudlet computing support. The sensors are embedded in the carpet to collect the waveform when people traverse the carpet. The measurements are sent to the Cloudlet nearby for future analysis and making real-time decisions with minimum delay.

2.2.4. Information System

In [36], Otomo et al. developed an in-vehicle Cloudlet computing disaster information system. This system aims to handle critical network situations flexibly. To achieve this goal, the authors introduced mobile Cloudlet computing, which enables rapid sharing of disaster information.

2.3. Fog Computing

The OpenFog Consortium Architecture Working Group [37] defined fog computing as a *"horizontal, system-level architecture that distributes computing, storage, control and networking functions closer to the users along a cloud-to-thing continuum"*. Compared with other edge computing architectures, such as MAEC and Cloudlet computing, fog computing focuses on the communication and cooperation among decentralized devices, such as IoT devices. Thus, fog computing services are closer to the terminal devices and more efficient. This

primary feature can help provide quality and efficient services [38]. Fog computing usually involves a large number of ubiquitous devices. The service of fog computing can be accessed through connected devices at the edge. Therefore, the nodes of fog computing have high mobility, and the servers can be placed at the edge or any specified location.

Fog computing is an expansion of classic cloud computing designed to address the challenges of latency and bandwidth. According to Das et al. [39], Sabireen et al. [40], Yi et al. [41], and Ai et al. [42], the primary features of fog computing are low latency—since fog servers are close to the end devices, it also results in shorter response times; real-time interaction—fog computing services can response in a short time frame; wide physical distribution—compared to traditional cloud computing, fog servers can provide decentralized services in any location; real-time analytics—this involves collecting and acting on data as it is transferred to the fog nodes rather than sending it to a central point and waiting for processing. Fog nodes include lightweight computing units that handle small computing tasks. The central cloud servers only need to receive the essential data and complete complex computing tasks. Data processing becomes more efficient with less bandwidth usage and latency.

Figure 5 shows an overall hierarchical architecture of fog computing. The bottom layer is closest to the end-user and is comprised of various end devices, such as IoT sensors, mobile phones, intelligent vehicles, and others, which are geographically distributed. These devices can sense and gather data from the physical environment and transmit it to the upper layer. The fog layer consists of a large number of fog nodes, such as routers and switches, which are responsible for data transmission, storage, and computation. Fog nodes can be installed in dedicated locations or on a moving carrier [43]. The computational ability of these fog nodes allows them to handle real-time analysis and provide service with low latency. Furthermore, the proximity of the fog layer to the terminal devices enhances communication efficiency. It connects with the cloud layer and delegates more complex and time-consuming tasks to the cloud center. The top layer comprises multiple powerful servers and storage devices. The cloud data center supports comprehensive computation and storage of a large amount of data. Tasks executed in this layer are usually complex and non-latency-sensitive. Nowadays, various commercial cloud services such as DigitalOcean, Apple iCloud, and Amazon EC2 are available [44].
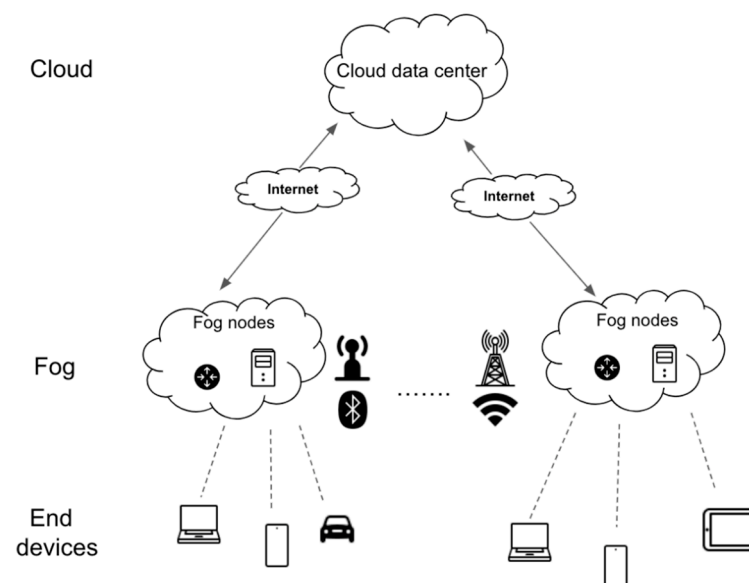

Figure 5. The overall hierarchical architecture of fog computing.

A large number of applications are developed by using fog computing architecture. We surveyed and summarized them as follows.

2.3.1. Healthcare

Y. Cao et al. proposed a fog computing-assisted system called FAST to monitor falls for stroke mitigation [45]. This system developed a new non-linear time series analysis algorithm and split the computing tasks between the fog devices and the server in the cloud. Vilela et al. [46] developed a fog-assisted health monitoring system. In this fog-based system, the data are stored and analyzed locally. The results show that this approach relieves data traffic congestion in the network and enhances the security of patients' information. Azimi et al. proposed a fog-assisted computing system called HiCH [47]. This system is designed for remote health monitoring and partitions health data analytics into two parts. The central part of the cloud provides service for heavy training procedures and outsources the trained hypotheses, which are updated periodically to the fog nodes; [48] presents a fog computing interface (FIT) for clinical speech data processing. This interface is a low-power embedded system that collects and analyzes speech data before transferring speech features to a central cloud.

2.3.2. Smart City

Thakur et al. [49] studied vehicular congestion identification techniques based on fog computing. Communication in the system becomes more effective, allowing more nodes to be involved in communication without affecting performance. Pereira et al. [50] proposed an architecture for the development of fog computing applications in a vehicular ad hoc network (VANET) environment. Furthermore, they presented two fog computing applications for this system, and their results showed that the fog applications can provide reliable real-time information while minimizing traffic. Serdaroglu et al. proposed a fog computing-based air quality monitoring system where air quality monitoring stations are located in the edge layer and provide sensor data to the fog layer for data processing and calculating [51]. Aliyu et al. [52] proposed a fog computing-assisted path planning system for smart shopping. Fog nodes are placed in the shopping mall and collect the data from shoppers' mobile devices. The fog layer simulates and recommends promotions for customers. Experiment results show that customers receive the recommendations in a shorter time and shopping speed is noticeably increased.

2.3.3. Video and Game Analytics

Video analytics always involve intensive computation or large bandwidth demand. To address this issue, the authors in [53] proposed a system called Latency-Aware Video Edge Analytics (LAVEA) based on an edge computing platform. This system offloads computation between clients and edge nodes, fosters collaboration among neighboring edge nodes, and delivers low-latency video analytics to nearby users. Cloud gaming is an emerging technique, but it suffers from high response latency and bandwidth costs. Lin et al. [54] proposed a fog computing system named CloudFog that can handle the challenges brought by massively multiplayer online gaming. CloudFog uses super nodes as "fog" to connect users and the cloud. The cloud is responsible for intensive computations and transmits updated data to supernodes. These super nodes are responsible for creating game videos to be streamed to players.

2.3.4. Intelligent Traffic

With the development of artificial intelligence technologies such as context awareness, intelligent traffic has become an important component of a smart city. Meanwhile, fog computing can be introduced into the intelligent traffic system for better performance. The authors in [55] presented a project called Laboratoire Recherche Informatique Maisonneuve (LRIMa) city, which is a fog computing-based smart city with integrated self-driving cars. By adding a fog layer between the physical layer and the network layer, traffic lights and smart cars can realize real-time interaction in this system. Awaisi et al. [56] proposed a fog-enabled efficient car parking architecture with three tiers: physical tier, fog tier, and cloud tier. Cameras in the first tier take pictures of the parking area and send them to the

fog nodes. The fog nodes receive and share the information with each other. After a certain period, the fog nodes communicate with the cloud server and send the essential data to the cloud. The experimental results show that this system reduces latency and overall network usage significantly.

In summary, this section introduces three classic edge computing architectures and their corresponding applications. The primary differences among these edge computing architectures lie in the composition of the intermediate infrastructure. MAEC utilizes base stations as edge servers. Data processing usually occurs directly on the end devices or an edge node near the end devices. In Cloudlet computing, Cloudlets can be considered small cloud data centers with greater mobility at the network's edge. Fog computing employs clusters of connected devices, including routers and switches, as edge servers. These devices in the fog nodes are responsible for data transmission, storage, and computation. Table 1 lists the references in this section.

Table 1. Reference Table of Edge Computing Architecture.

Architecture	Application Area	References
Multi-Access Edge Computing	Healthcare	[21]
	Smart City	[22,23]
	Video Analytics	[24,25]
	Connected Vehicles	[26]
Cloudlet Computing	Face Recognition	[31]
	Healthcare	[32]
	Smart Homes	[33–35]
	Information System	[36]
Fog Computing	Healthcare	[45–48]
	Smart City	[49–52]
	Video and Game Analytics	[53,54]
	Intelligent Traffic	[55,56]

3. Review of Edge Computing Technologies

The emergence of edge computing has accelerated the development of the IoT and plays a pivotal role in an intelligent society. In addition to edge computing architecture, the technologies used in designing edge computing applications have become popular research topics within the intelligent community. This section mainly includes reviews of computational offloading, resource placement, traffic offloading, caching, energy efficiency, and storage.

3.1. Computational Offloading

In edge computing, computational offloading refers to the technique that transfers heavy computation tasks to nearby edge servers [57]. With the increasing number of resource-demanding applications, improving hardware in mobile ends and networks will still not be able to keep up with the trend in demand. Therefore, computational offloading has gained attention in edge computing research. Many researchers have studied computational offloading to resource-rich edge servers. Computational offloading is the key technology to enable MAEC to run complex applications on edge equipment by delivering compute-intensive tasks to separate edge servers. There have been many related research achievements mainly discussing offloading strategies.

In 2016, Zhang et al. [58] proposed a mobile edge computing-based offloading framework in a cloud-enabled vehicular network. In this framework, an efficient offloading strategy is designed. Meanwhile, considering the limitation of the edge servers and latency tolerance of the computing tasks, a contract-based computing resource scheduling scheme is designed. The experiments show that the proposed scheme improves the performance of the MAEC utility.

In 2020, Zhang et al. [59] also focused on task offloading in vehicular edge computing networks. Various delay-sensitive vehicular applications have emerged due to the rapid development of vehicular networks. MAEC is becoming a promising paradigm, benefiting vehicular edge computing networks by offloading the vehicles' compute-intensive tasks to nearby edge nodes. The authors introduced fiber-wireless technology to address load-balancing issues and proposed a software-defined networking (SDN)-based load-balancing task offloading scheme in Wi-Fi-enhanced vehicular edge computing networks. This scheme uses SDN to support centralized network and vehicle data management. The experiment results demonstrate that this scheme can achieve superior performance on delay reduction.

Real-time analytics of video content are widely recognized as a prime application for edge computing. They often involve heavy computing tasks and a large amount of data. In 2018, Hung et al. [60] proposed VideoEdge, which is a hierarchical architecture. This architecture includes cameras, clusters, and the cloud for video analytics targeting query optimizations. The architecture presents a prominent demand for determining the optimal balance between various resources and precision, thus reducing the search space. VideoEdge, for each video inquiry, chooses the most suitable amalgamation of algorithmic elements and distributes them across diverse clusters. VideoEdge operates under the assumption that camera-based computing is absent, shifting the entirety of computer vision processing to secluded clusters.

Xu et al. [61] proposed a trust-aware task offloading method (TOM) for video surveillance in edge computing-enabled Internet of Vehicles. This method aims to minimize the response time of the services and achieve the load balance among the edge nodes. By analyzing the process of video tasks, the authors formulated the problems of task offloading, time cost of services, and privacy entropy as a multi-objective optimization problem. To address the task offloading issue, they chose SPEA2 (improved Strength Pareto Evolutionary Algorithm) [62] to solve the objective problem of task offloading. The experiment results show that TOM achieves better performance on edge resource utilization and load balance among the nodes.

3.2. Resource Placement

The geographical distribution of resources is one of the most important components in edge computing as it supports the mobility of edge computing applications. Mobile ends collect data and transfer it to the nearest edge computing nodes. The cloud center supports application mobility by anchoring the server's position and transferring data to the server through the network.

In the area of resource placement, some works focus on the placement of edge nodes. To calculate the cost and average latency of the edge computing network, factors such as the location and the number of edge nodes must be considered. The study [63] proposed the Cost Aware Cloudlet Placement in Mobile Edge Computing (CAPABLE) strategy, considering both the Cloudlet cost and average end-to-end delay. This strategy also includes a Lagrange-based heuristic algorithm and a workload allocation scheme to minimize the mobility delay. The results show that CAPABLE minimizes the average end-to-end delay between users and their Cloudlets while also reducing the cost of the Cloudlets. In another study [64], researchers presented a framework to address the edge server placement problem. The goal of this framework is to optimize server placement strategies and reduce the costs of deploying edge computing networks.

Nowadays, data-intensive tasks that need large storage space and rich calculation resources have become common in edge computing. Current research usually focuses on transmitting data from end devices to edge servers but ignores the data storage on lightweight edge servers with limited resources. Jin et al. [65] presented an efficient graph-based iterative algorithm for edge-side data placement problems. Compared to the traditional storage strategy, the proposed algorithm increases the cache hit rate significantly.

Geographical mobility leads to another challenge in effectively managing hardware resources. Virtualization is one of the fundamental edge computing technologies to address this issue. Virtualization technology, usually in the form of virtual machines (VMs) or containers, provides flexible and reliable management for edge computing. In [66], the authors designed a complementary algorithm for dynamic VM placement. The proposed algorithm decides whether there is a more suitable place for the VM allocation before the offloaded task is processed at the VM. The algorithm is based on the predicted mobility of users and the load of the base stations' communication and computation resources.

3.3. Traffic Offloading

Traffic offloading refers to offloading traffic that meets specific offloading rules to mobile edge networks. It is vital in mobile edge computing as it focuses on providing high bandwidth and low latency.

Abdelwahab et al. [67] presented an edge cloud architecture called REPLISOM. REPLISOM is a long-term evolution (LTE)-aware edge cloud architecture with optimized LTE memory replication protocol. This protocol enables end devices to transmit the memory replica to its neighbor devices by using device-to-device technology. The receiving devices compress the received replicas. The edge servers pull the completed compressed data from the receiving devices. This architecture alleviates LTE bottlenecks and effectively schedules memory replication to avoid resource-allocating conflicts. Evaluation results demonstrate that this architecture can reduce delay and cost for traffic offloading of IoT applications.

To alleviate network bottlenecks and reduce data latency, Kumar et al. [68] investigated vehicular delay-tolerant networks (VDTNs). This architecture enables effective data transmission to various devices using a store-and-carry-forward mechanism. Massive computations, such as decisions about charging and discharging, are performed by mobile devices at the edge of the network. Experimental results demonstrate an increase in throughput and a decrease in response time and latency.

Wen et al. [69] proposed a further improvement of communication in mobile edge computing by introducing an energy-efficient device-to-device (D2D) offloading network scheme. The D2D technique is used for traffic offloading as well as task balancing. Experimental results show that the proposed MEC-D2D model and MEC-D2D-Relay model reduce energy consumption and inter interference. Additionally, both models can avoid traffic congestion and provide a rapid response to end users.

3.4. Caching

Edge computing caching includes base station caching, distribution networks, and transparent caching, all of which significantly impact content distribution efficiency and service quality. Unlike traditional methods, edge computing caches can store content in edge nodes, enabling users to access data nearby instead of transmitting it from the cloud center. Additionally, edge computing caches reduce network delay and enhance service quality.

Li et al. [70] proposed a cache-aware task scheduling strategy in edge computing to address issues related to improper placement and utilization of caching. They obtained an integrated utility function considering data transmission cost, caching value, and cache replacement penalty. Furthermore, they presented a cache locality-based task scheduling method, treating the task scheduling problem as a weighted graph affected by the positions of required data. Experimental results demonstrate that the proposed task scheduling algorithm performs better than other baseline algorithms in cache hit ratio, data transmission time, response time, and energy consumption.

Zhang et al. [71] illustrated that edge caching can reduce the burden on the backhaul network, but existing works often treat storage and computing resources separately, ignoring the mobility characteristic of edge caching and portable end devices. They proposed a cooperative edge caching framework for 5G networks, utilizing edge computing resources to enhance edge caching capability. In the proposed framework, smart vehicles are employed as collaborative caching nodes for bringing contents to end equipment and sharing

content cache tasks with base stations. The experiments show that the proposed framework alleviates content access latency and improves the utilization of cache resources.

Xia et al. [72] investigated the collaborative caching problem in the edge computing environment, aiming to reduce the data caching and migration cost. This collaborative edge data caching problem (CEDC) is formulated as a constrained optimization problem. An online algorithm called CEDC-Online (CEDC-O) based on Lyapunov optimization is proposed.

3.5. Energy Consumption

Edge computing reduces latency, enhances security, and offloads heavy computation from the cloud to the network edge. While energy consumption in cloud centers has been extensively studied, research on the energy efficiency of edge computing is still needed. Communication among edge devices, servers, and cloud centers is complex, making energy efficiency a hot topic in edge computing.

Zhang et al. [73] presented an energy-aware offloading scheme for optimizing resource allocation. The core technology of this scheme is an iterative search algorithm combining interior penalty functions. This algorithm takes the residual energy of smart devices' batteries as the weighting factor of power consumption and latency. Results demonstrate that the proposed algorithm can find the optimal solution for energy consumption.

In [74], Li et al. studied the energy consumption of energy-aware edge server placement. This problem is formulated as a multi-objective optimization problem. An energy-aware edge server placement algorithm involving particle swarm optimization is investigated to find the optimal solution. Experiments indicate that this algorithm can improve the computing resource utilization and minimize the energy consumption.

Hao et al. [75] introduced green energy sources such as wind energy into edge devices. Nodes are divided into clusters, each containing several edge nodes to ensure a minimum distance between nodes in the cluster. A scheduling heuristic algorithm is implemented to schedule tasks and transfer energy based on the clustering method. Experiment results show that the proposed method reduces total energy consumption both in and out of the system.

3.6. Efficient and Safe Storage

The limited storage resources of end devices tend to affect user experience. Therefore, efficient and secure storage solutions are worth investigating in the field of edge computing.

Xing et al. [76] proposed a distributed multi-level storage (DMLS) model with a multiple-factors least frequently used (mLFU) algorithm to address storage limitations. In this model, storage levels are composed of terminal devices at the edge. The mLFU is utilized to upload data from the current device to higher storage levels and subsequently remove this data from the device.

In summary, this section outlines popular edge computing technologies and state-of-the-art research. Computational offloading and traffic offloading are two topics that leverage edge computing architecture to extend computing resources and bandwidth. The resource placement subsection discusses how to strategically deploy edge nodes. Caching, storage, and energy consumption pertain to hardware in edge computing. Table 2 lists the references in this section.

Table 2. Reference Table of Edge Computing Technologies.

Technologies	References
Computational Offloading	[58–61]
Resource Placement	[63–66]
Traffic Offloading	[67–69]
Caching	[70–72]
Energy Efficiency	[73–75]
Efficient and Safe Storage	[76]

4. Review of Edge Computing in Power Systems

Power systems are large-scale and comprehensive electrical networks that support critical electricity services [77]. In recent years, intelligent monitoring, control, and computational equipment have emerged, transforming traditional power systems characterized by unidirectional communication and centralized energy production into smart grids. These smart grids incorporate bidirectional communication and decentralized energy sources, including renewable energy, and utilize intelligent monitoring and control technologies to enhance grid efficiency, reliability, and sustainability. This technological shift is pivotal in addressing the growing energy demands and decarbonization challenges. This section reviews the applications of edge computing within smart grids to illustrate how it offers new opportunities to solve the issues brought by these modern systems.

4.1. Introduction of Smart Grids and Grid Edge

Smart grids are advanced supply-to-demand networks that automate and decentralize power flow [77], constituting a cyber–physical system that integrates computation, communication, and control (3C) technologies [78]. The IEEE [79] defines smart grids as "*self-sufficient systems which allow integration of any type and any scale generation sources to the grid that reduces the workforce targeting sustainable, reliable, safe and quality electricity to all consumers*", while the U.S. Department of Energy [80] defines the grid edge as "*The grid edge is where buildings, industry, transportation, renewables, storage, and the electric grid come together. More specifically, it's the area where electricity distribution transitions between the energy utility and the end user*".

The transition to smart grids provides numerous benefits, including more efficient electricity transmission, quick and more accurate detection and restoration from power disturbances, reduced cost for power utility management, lower electricity rates, and better integration of large-scale renewable energy sources [81].

The general structure of the smart grid can be classified into three layers: the user layer, the information system layer, and the physical system layer [78]. The user layer serves as an interface for system operators to interact with the system. The information system layer handles transmission, receives data from the physical system layer, and processes it. The physical system layer consists of multiple sensors, executors, and transmission lines.

Smart grids encompass a vast array of components, including power generation, transmission, distribution, and consumer interface components. It can be further partitioned into different function components. The smart device interface component is responsible for managing smart devices connected to the electronic devices. The storage component is related to the energy storage capability, improving reliability in cases of inconsistency from renewable energy sources and mismatches between peak consumption. The transmission component is the backbone of the power system connecting main substations and load centers. The monitoring and controlling components are used for surveillance, prediction, and handling of reliability issues, instability, and congestion. Finally, the demand-side management component aims to modify consumer demand to reduce costs by reducing the use of expensive generators and delaying capacity addition.

While the emergence of the smart grid brings numerous benefits, it also presents challenges. The increasing number of smart meters and other smart equipment results in growing communication demands, potentially leading to high latency issues as end devices communicate with the central system. Edge computing can help mitigate these challenges by leveraging its advanced features. As redundancy of the elements increases in a smart grid, a comprehensive Smart Grid Architecture Model (SGAM) can help determine how to design edge computing deployed smart grid architecture. A well-designed architecture is the base of edge computing-enabled smart grids [82].

In recent years, a more complex and comprehensive concept known as the grid edge has emerged. The grid edge encompasses various technologies implemented near the customer side or at the ends of power grids, involving building electrification, distributed power generation and storage [83], data storage and transmission, demand-side manage-

ment [84], power transmission, and distribution, among others. Typical research topics include connected utilities and infrastructure, energy storage, virtual power plants, distributed energy resources, cybersecurity and data privacy, and more. These emerging topics indicate that the grid edge will be studied more extensively, with both academia and business energy companies updating their strategies to adapt to disruptive solutions such as smart meters and smart grids becoming increasingly prevalent in the market. A study reports that 75% of enterprise data will be produced at the grid edge by 2025 [84]. Meanwhile, experts from Red Hat predict that within the next three years, IT budget costs will account for 30% of the total [84]. Research on the grid edge is necessary and well worth the investment.

The primary goals of edge grid technology programs are to create new energy architectures that address decentralization and handle the increasing volume of data. Historically, electricity was generated by the centralized utilities and transmitted to end users. As modern power systems evolve, traditional energy models no longer suffice. Decentralized power centers at the grid edge offer similar benefits with fewer risks and lower costs, motivating both academia and industry to focus on decentralization and grid edge research. By shifting to smaller hubs near the consumer side, energy loss and risks can be reduced, and distribution centers can be more flexible and easily maintained.

Additionally, the emergence of IoT, smart meters, and other technologies has led to a data explosion, overwhelming centralized systems with data collection, transmission, and analysis. Consequently, the power industry prioritizes grid-edge innovations. Significant projects such as the BrooklynQueens Demand Management program (BQDM) [85] and California's Demand Response Auction Mechanism (DRAM) [86] exemplify successful grid edge initiatives [84]. Well-designed energy models based on the grid edge can also decrease the costs of energy transportation and storage and improve the stability of the power supply.

As enterprises and countries race to realize digital transformation in the energy sector and net-zero emissions, AI deployed at the edge (edge AI) becomes a popular technology. Edge AI can effectively manage distributed energy resources [87]. Noteworthy AI [88] uses AI-enabled vehicle-mounted cameras to help monitor pole-mounted assets. Small boxes also attach to trucks with computation resources and communications gear in them. These boxes link to a processing unit in the cab to execute machine learning tasks [89]. Siemens Energy uses AI deployed at the edge of power plants to realize autonomous management [90].

Many researchers are exploring the use of edge computing technology to enhance power system applications. The following applications have been reviewed in this paper:

- Power Grid Distribution Monitoring;
- Smart Meters Management;
- Data Collection and Analysis;
- Anomaly Detection;
- Measurement Placement;
- State Estimation;
- Energy Storage;
- Resource Management;
- Security of Grid Edge Management System;
- Renewable Energy Forecasting.

4.2. Power Grid Distribution Monitoring

Power grid monitoring is one of the most important research topics in smart grids today. With advancements in power grid technology, power sources have diversified. Devices for renewable energy, such as solar energy and wind energy, have a varied geographical distribution. Furthermore, the emerging smart end devices used in smart grids have made traditional manual inspection inadequate for ensuring safety and efficiency. Smart grid monitoring and control have become increasingly complex, necessitating real-time

responses. Many researchers have focused on this issue and proposed various applications to address these challenges.

In 2018, Huang et al. [91] emphasized the importance of power grid monitoring in preventing severe safety accidents. Recognizing that traditional manual detection cannot meet the needs of modern power grids, the authors proposed an edge computing framework for real-time monitoring. They developed this framework by moving part of the computation from the central cloud to the edge servers. Their experiments showed that the detection delay was reduced by up to 85% compared to cloud-based solutions.

Monitoring real-time smart meters is another popular topic. In 2020, Tom et al. [92] focused on AMI in smart grids. Given that smart grid infrastructures are geographically distributed, there is a demand for effective monitoring and control systems. A good routing protocol is crucial for the metering infrastructure to communicate effectively with the fog router. A standard routing protocol for IPv6 over Low Power Personal Area Network (6LoWPAN) is the routing protocol for Low Power Lossy Area Network (RPL). Smart meters within the 6LoWPAN network communicate with fog routers, which results in nodes far from the fog routers having low packet delivery ratios and high delays. The authors proposed an advanced RPL scheme to address this issue. Instead of communicating with the fog router directly, aggregator-based RPL nodes were set between edge nodes and the fog router. Performance evaluations showed that this scheme effectively increased packet delivery ratios and reduced end-to-end delays.

Sun et al. [93] proposed an edge computing node planning model for real-time transmission line monitoring. Monitoring transmission lines is crucial to ensure the stable operation of the power grid. The emergence of real-time online monitoring services enhances the safety of the transmission lines, but it also introduces a high latency requirement. Edge computing can bring the edge nodes closer to the terminal, thereby reducing latency. In their paper, an edge computing node placement model was established, and a genetic algorithm based on a predator search strategy was proposed to overcome the shortcomings of the original genetic algorithm. Simulation experiments demonstrated that this improved genetic algorithm performed better in planning the placement of edge nodes.

The work presented in [94] focuses on the communication system models used for voltage profile monitoring and power loss estimation in smart grids. The author implemented and compared two different architectures: cloud-based and cloud–fog-based. Experimental results showed that the cloud–fog-based approach significantly reduced the total simulation time and the data size transferred to the cloud.

4.3. Smart Meters Management

Energy resources play a crucial role in the development of a country and its economy. A stable energy source can provide significant benefits. To achieve this goal, governments have been making efforts to build and deploy smart grid infrastructures in recent years. As an essential device to measure and record the energy consumption of the customer side, smart meters need to be optimized for more efficient and stable power systems. This subsection presents the state-of-the-art edge computing-based applications in smart grids.

In smart grids, smart meters can help to detect anomalies in real-time quickly and effectively. However, sending data within a short time slice is not normal because of the bottleneck of the communication network and storage media. Utomo et al. [95] proposed prediction techniques by combining deep neural network (DNN), support vector regression (SVR), and k-nearest neighbors (KNN). To predict anomalies in the next few weeks, the timestep is set as one day. This can help users to check their usage and decide whether to prepare sufficient resources or not. The proposed techniques also involve Edge Meter Data Management System (MDMS) and Cloud-MDMS in model training.

Smart meters are typical end devices that can collect and send energy data. The usage of smart meters can establish a close relationship between smart grids and cyber-physical systems. With the development of the smart grid, an increasing number of smart meters have been installed. The malfunction detection of large-scale meters has become an issue.

Liu et al. [96] proposed a meter error estimation method and studied a low-voltage energy system model. The proposed method includes a decision tree to sort data with different loss levels. It also generates data clusters with different energy usage behavior. Then, a data matrix can be established, and a recursive algorithm is used to calculate the equation and estimate the meter error. By comparing the regulation threshold and the meter error, the malfunctioning meter can be detected. Furthermore, this approach can be applied in an edge computing environment.

Kumari et al. [97] focused on transferring smart meter data from consumers to the operator within the given time with minimum energy consumption. The authors proposed a smart metering system using edge computing in Long Range (LoRa). All devices in a single house are connected to a smart meter. The edge device and the LoRa node are responsible for processing and transferring the data collected by smart meters. The energy multivariate time series are considered as the energy consumption of various electric devices. At first, the system uses a deep learning-based compression model to reduce the size of the time series. Then, it finds the optimal energy time series that can decrease energy consumption. Finally, an algorithm is adopted to obtain the appropriate spreading factors to transfer the time series from consumers to the operator within the given time. The experiments show that this system can transfer the time series within the given time with higher energy efficiency.

In recent years, the computing capabilities of IoT devices have significantly grown, and processing data in the end devices has become possible. The work in [98] presents a smart metering system that can process data analysis on the smart meter where it is produced. This system is based on a multi-core edge computing architecture. The experimental results show that this architecture reduces the processing time.

As the penetration of smart meters and the diversity of participants increase, allowing users to obtain and use the information behind the meter will be highly beneficial. To achieve this goal, the concept of an unbundled smart meter (USM) was introduced in the European Nobel Grid project [99]. The USM has two components: a smart metrology meter and a smart meter extension. The smart metrology meter, a sensor module, includes interfaces that enable users to read real-time information. The smart meter extension is a framework embedded in the USM that supports various new functionalities. In [100], Qin et al. proposed an artificial intelligent agent for USM based on deep learning. This agent combines deep learning models and real-time data from USM to help customers and utilities manage their energy usage more effectively. Meanwhile, the spatiotemporal decomposition technique involving different deep learning models in time series is deployed in the agent for load and photovoltaic power forecasting. The experiment results show that this spatiotemporal decomposition agent performs well in controlling operating costs and battery degradation costs.

4.4. Data Collection and Analysis

An advanced smart metering system is essential for the success of the smart grid. This system is one of the important components for data collecting and analyzing in smart grids. Hence, it plays an important role in ensuring the safe, stable, and efficient operation of smart grids. In this subsection, the emerging applications for data collection and analysis using an advanced smart metering system will be discussed.

Connectivity verification of the distribution system is an urgent problem. To solve this problem, Si et al. [101] introduced a cloud-based collaboration mechanism to determine outlier users and valid connections. In this paper, the authors came up with an affinity propagation clustering-based local outlier factor (AP-LOF) algorithm that can effectively identify and verify the voltage outlier. Moreover, they set up a mechanism in the cloud center to correct the identified outliers. The experiments are based on actual smart meter data. The results show that the performance of this algorithm is better compared with traditional methods. Additionally, the calculation efficiency is improved significantly because of the cloud–edge collaboration scheme.

Improving the analyzing capability of the smart meter is another notable research topic. Sirojan et al. [102] presented that traditional smart meters are only able to measure and show the digital number of energy usage. To enable the smart meter to function in modern advanced metering systems, the authors proposed an embedded edge computing paradigm in the smart meter. This paradigm improves accuracy, latency, and bandwidth significantly by bringing data analytics to the smart meters.

4.5. Anomaly Detection

Anomaly detection, also known as outlier detection, is a process that collects and observes data to find behaviors that deviate from the standard pattern. Due to the wide usage of smart meters, anomaly detection of smart meter data has attracted much attention from academia. Abnormal energy consumption in daily life happens very often, such as electricity leakage and theft. Therefore, anomaly detection of meter data can benefit society and the economy significantly.

One of the detection methods is centralized detection. This method, which combines multiple techniques such as big data processes, analyzes the smart grid data uniformly. The infrastructure, such as smart meters, measures consumers' energy consumption and sends the measurements to the data center for analysis. For future processing, the centralized facilities execute the detection algorithms to analyze the large volume of data gathered from electricity smart meters and these algorithms have great performance in detecting anomalous power consumption. Cui et al. [103] focused on centralized anomaly detection in school electricity facilities. The authors investigated hybrid anomaly detection models and collected electricity consumption data for analysis. According to the evaluation, the system can effectively detect the anomaly electricity consumption in the school. Silva et al. [104] proposed a centralized anomaly detection method based on Long Short-Term Memory (LSTM) and Negative Selection. This method can be applied to anticipate the anomalies in electricity consumption. Meanwhile, this method can also predict the occurrence of anomalies and monitor power consumption in real-time.

Another commonly used detection method is decentralized detection. The traditional centralized anomaly detection methods rely on installing many electricity meter devices in households. The power consumption data are measured and collected by these meters and transmitted to the centralized data center for future processing and analysis. In the recent smart grid architecture, a large scale of smart devices are distributed across various facilities over a large geographical area for monitoring power consumption. It is difficult for traditional centralized detection methods to handle such a large amount of data generated by smart meters. In this case, edge computing has become one of the solutions to reduce latency and provide better performance in data processing. Liang et al. [105] proposed an anomaly detection method with edge computing architecture. Instead of applying the anomaly detection model in the data center, the authors distributed the model on the edge node devices. Moreover, to reduce the delay, two-way communication is adopted in this method. The experiment results show that this method greatly reduces the communication delay and improves detection accuracy. Zheng et al. [106] presented an edge computing-based electricity theft detection method. Electricity theft by low voltage (LV) users could cause power loss and electric shock. It is essential to monitor and identify anomalous users of electricity theft. However, smart meters of LV users occasionally fail to update the data to the centralized advanced metering infrastructure. In the proposed approach, the Granger causality test is applied in the distribution transformer unit with edge computing. Since the distribution transformer unit collects the data without distortion, the proposed method can prevent the distortion caused by updating failure. Furthermore, fog computing can be introduced as another decentralized paradigm for anomaly detection. Jaiswal et al. [107] proposed a hierarchical fog computing architecture to develop anomaly detection machine learning models. The proposed anomaly detection consists of two parts: model training and anomaly detection. The evaluation results confirm the efficacy of the proposed architecture.

4.6. Measurement Placement

MEC extends a cloud computing scheme and leverages servers near end-users at the network edge to provide a cloud-like environment. An appropriate measurement placement strategy plays a crucial role in the performance of such service-based applications. The features of modern smart grids, such as large-scale geographical distribution, bring challenging issues to measurement placement. In this subsection, several research topics on measurement placement are summarized and discussed.

Zhao et al. [108] focused on low-delay resource scheduling in power systems. The paper presents that as an increasing number of smart devices are used in smart grids, the massive data and calculations become heavy burdens for the power system. To improve processing efficiency, the authors proposed two heuristic algorithms combined with edge computing architecture. For the virtual machine sequence issue, sorting the virtual machines with the critical path algorithm is ideal for reducing the computing time. The second stage is to use an enhanced best-fit algorithm to improve the placement strategy, avoiding an increase in computing time. The experiments show that this two-stage algorithm ensures the optimal placement of virtual machines and effectively shortens the computing time of the power system.

Fault detection plays a primary role in modern smart grids. In paper [109], a framework based on the phasor measurement unit (PMU) and edge computing is proposed for fault detection and localization. In this framework, PMUs with embedded personal computers are placed at a primary substation and a secondary substation at the end of a feeder. This framework makes the fault detection and localization perform at the edge of the local network. The communication delay and the data loss are eliminated.

4.7. State Estimation

In modern power systems, state estimation (SE) is a necessary approach to monitor power grids. SE is a method to process the imperfect measurements and find the actual values of the unknown variables. It is a digital scheme that can estimate the true state of the power system. Modern power systems perform many functions, such as generating and transmitting electricity across multiple geographic areas. Computer-based management systems have emerged for controlling and managing such complex systems. Power systems typically are divided into several areas. Different areas are interconnected with each other. All areas need to keep the frequency the same under steady-state conditions [110]. However, power systems constantly suffer from disturbances covering a wide range of conditions. Therefore, real-time monitoring and control are essential functions in power systems. SE can provide real-time data for many of the central control and dispatch functions in a power system [111].

In power systems, there are always some imperfect measurements that are considered unknown variables. SE can estimate the true values of these unknown variables by using statistical criteria. With the development of the smart grid, the volume of the measuring data is increasing. In this situation, real-time control requires a wider bandwidth and more computing resources. To solve this issue, the state estimation can be executed at the edge nodes in the local area. Then, the estimated results can be updated in the control center. Edge computing is an ideal architecture to achieve this goal.

Meloni et al. [112] proposed a cloud–edge-based architecture for SE in modern smart grids. This solution combines cloud resources and edge computing advantages. Meanwhile, virtualization techniques are used to split the processing of measurement data from the physical devices. The traditional evaluation of the state of the power grid is performed at a slow rate and is suitable for steady-state operating conditions. The increasing scale of the power grid challenges power management. Therefore, the proposed system includes sensing devices such as PMUs that can dynamically monitor and control the system and properly handle anomalous states. This effective wide-area measurement system is based on PMUs and is bandwidth-consuming. To improve accuracy and reduce delay, edge computing is introduced. The edge devices in the network are considered micro-cloud

servers to host the advanced processing functions and application modules. The results show that this cloud–edge-based architecture can ensure the accuracy and latency of the estimation. The bandwidth is greatly reduced even when the PMUs execute full operating estimation. In another work, Kuraganti et al. [113] proposed a distributed hierarchy-based framework to ensure the SE data is not attacked and manipulated. Typically, the data for SE are collected from the PMUs and transmitted to a fixed center for future processing. The proposed framework guarantees that both data aggregation and SE are executed on random devices. The simulations on the Institute of Electrical and Electronics Engineers (IEEE) 5-bus system and IEEE 118-bus system show that the framework can observably protect the SE data.

4.8. Energy Storage

An increasing number of wide-range power outages have become more frequent in recent years due to drastic climate change. Nowadays, extreme weather happens more frequently, and these conditions challenge the stability and recovery capability of the power system. The impact of power outages is more significant than before. To enhance the reliability of the power system, Chuangpishit et al. [114] presented an advanced mobile energy storage system (MESS) to enhance the resilience of the power system. MESS can be considered a primary technology to offer a clean alternative to diesel or gas generators and provide emergency outage management. Typically, the MESS is small in size and cannot supply all the critical loads during the outage recovery time. Meanwhile, there are two more challenges: reconfiguring the customer connections and dedicating the backup energy storage system; the increasing size and number of devices are considered critical loads. As the technology of MESS evolves, the system size and the grid scale are growing rapidly. The article introduces several MESS use cases with planned or unplanned power outages. It also shows the business benefits the MESS can bring. The results indicate that MESS is an ideal power supply during recovery time. However, MESS is dependent on geography and some other distribution system characteristics. Utilities should use MESS based on their conditions and requirements.

4.9. Resource Management

Since the grid edge is a comprehensive concept covering a series of resources at the customer side, behind-the-meter (BTM) resources at the grid edge have become a popular topic in recent years. In [115], Y. Y. C. Zhang illustrated that BTM resources are treated as a primary component of the power grid. These resources, such as DERs and flexible loads, are important during the traditional power systems' transition to net-zero emissions and 100% renewable generation. Therefore, monitoring and forecasting these resources are critical goals in power system management. This paper focuses on discussing the gaps and issues of grid edge visibility. The gap in this paper is considered as "*the deficiency in the performance of a grid entity's responsibilities (e.g., efficiency or reliability) as a result of limitations in either the existing sensing and measurement technologies or the surrounding institutional frameworks or standards*". The gaps in grid edge visibility include four categories: weather forecasting, grid edge monitoring, data standards, and stakeholder obstacles.

The first gap is weather sensing and forecasting. Accurate real-time forecasts and weather monitoring play an important role in forecasting grid edge DERs and the net load. The traditional method relies on third-party weather forecasting data, which are collected on a very large spatial and temporal scale. To improve the accuracy and reduce latency of the weather data, one solution is to develop local weather monitoring sensors. The local weather monitoring sensors at the grid edge can provide real-time weather data and benefit resource management. The second gap is the lack of real-time visibility of grid edge components. One avenue to address this issue is to sort the grid edge devices by type and by load. Different devices are suitable for using different monitors to collect data. The third gap is the lack of standard data formats among different applications. With the development of the grid edge resources, standard data can increase communication

effectiveness. Last but not least, stakeholder capability and interest also harm the grid edge visibility.

As distributed energy resources become the secondary side of the grid edge, distributed grid edge control has become a new challenge for utilities. For distributed utility management, volt and var are two primary parameters. However, objectives such as minimizing distribution loss, saving energy, and reducing peak demand are far from easy for existing controlling strategies to achieve. Therefore, Moghe [116] presented a distributed grid edge control by using autonomous fast-acting hybrid power electronics devices.

The first contribution is that the presented distributed controlling strategy is an "edge-up" architecture instead of the traditional "top-down" approach. Autonomous devices called the Edge of Network Grid Optimization (ENGO), are introduced to realize the "edge-up" strategy. ENGO devices are managed by a software layer called the Grid Edge Management System (GEMS) [Wärtsilä Energy Storage—GEMS Digital Energy Platform Available online: https://storage.wartsila.com/technology/gems/ (accessed on 27 June 2024)]. The ENGO-GEMS system provides an effective solution for utilities to manage the distributed grid and achieve the objectives mentioned above. Furthermore, a control principle, implemented with the coordination of set points between all ENGO devices and the major assets, was presented in the ENGO-GEMS system.

Due to the diversity of energy resources and increasing demand for energy, the way the power system produces and transmits energy is becoming more and more complex. The adoption of these new energy resources presents new grid management challenges. In recent years, artificial intelligence (AI) and machine learning have been introduced at the grid edge to ensure the reliability and resiliency of energy systems. In [117], Y.C. Zhang et al. proposed edge AI, an advanced AI technology that can handle the complex grid edge more efficiently. The connected physical devices near the customer are embedded with AI applications and are in charge of computation. Rather than completing the computation in the central data center, handling the data with the devices close to where it is produced can make the operation of edge devices more stable and reliable.

4.10. Security of Grid Edge Management System

Network-constrained energy management systems at the grid edge depend on the interconnection of a circuit segment to deliver and receive load measurement. However, this raises the risk of invisible false data injection attacks (FDIAs). To eliminate this risk, the paper [118] proposes a framework to detect the FDIAs on loads and replace the anomalous data with forecasted values. The detection algorithm in this framework comprises seven steps. The first step is to implement state estimation with the received measurements. Then, the bad data detection algorithm is proposed to check for anomalies in the load. If anomalous data are detected, the system will replace the bad data with the forecasted values. Otherwise, a data-driven autoencoder (AE) approach in another layer is responsible for identifying potential attacks in the measurements. If there is no indication that the measurements are attacked, the measured data can be used in a grid-edge energy management system. This security enhancement framework is tested by using an IEEE 13-bus system with three integrated DERs. The evaluation results show that the proposed framework can effectively mitigate the risk of FDIAs and enhance the resilient operation of grid-edge energy management systems. The emergence of inverter-based DERs prompts diverse renewable energy sources to integrate into the primary grid. Inverter-based DERs bring many considerable benefits, such as improving power quality by minimizing harmonics and responding rapidly to fault isolation. Although inverter-based DERs can provide improvements, there are still challenges that need to be resolved. The first challenge, as presented by Gao et al. [119], is that the inherent instability of renewable energy sources threatens the reliability of the system. The existing forecasting method still cannot predict the variance between estimated and real values, which can result in serious reliability issues. The second challenge is the stability of the system. Low inertia can reduce the system's stability margin. To address the limitations mentioned above, the authors

proposed a cyber–physical security assessment framework. The framework consists of a cyber–physical system model involving dynamic attributes of inverter-based DERs. The proposed framework was evaluated with IEEE 13-node and 123-node test feeders, and the results show that this framework demonstrates significant improvement in resilience and stabilization.

4.11. Renewable Energy Monitoring and Forecasting

In recent years, the shortage of energy resources has become a popular topic. It is urgent to solve this issue by improving the efficiency of energy usage and developing renewable energy resources. This subsection focuses on monitoring and forecasting the generation and consumption of power produced by renewable energy resources.

In recent years, the power facilities of renewable energy, such as photovoltaic systems, have been involved in a digital revolution. With the increasing scale of the distributed renewable energy systems, it is essential to develop a new computing paradigm in monitoring. In [120], Abdelmoula et al. proposed a framework for distributed photovoltaic systems monitoring and fault detection in a smart city. This edge computing framework enables the data to be processed at the edge of the network, reducing the time and bandwidth consumption. Four light machine learning models are tested and selected as the best performers and implemented in the edge nodes. The experiment results show that this framework effectively improves the accuracy of fault detection in photovoltaic systems.

In [121], Lv et al. focused on forecasting short-term electricity generation and consumption. In this paper, smart grid 2.0 is mentioned as the basic knowledge that refers to the next generation of power grid, including distributed renewable energy resources, bi-directional energy, and modern digital energy management systems. Smart microgrid is one of the techniques that can help with realizing smart grid 2.0. It can provide automated management of distributed renewable energy resources. To realize smart microgrids, integrating edge computing and AI (edge–AI) plays a key role. An edge–AI-based forecasting method is proposed in this article. This method includes a wind generation forecasting algorithm implemented in edge devices based on convolutional neural network (CNN) and gated recurrent unit (GRU) machine learning models, and an electric load prediction algorithm in end users' devices. Experiment results on real-world datasets from China and Belgium show that the proposed algorithms improve the prediction accuracy of wind power generation and consumption forecasting.

In [122], Nammouchi et al. discussed the energy management of microgrids. This paper aims to address the microgrid monitoring issue. The proposed edge–AI framework integrates machine learning models for forecasting power supply and demand at the edge of the smart microgrids. Experiments on real-time data under different scenarios demonstrate that the proposed framework can fit different types of microgrids and improve the flexibility and performance of microgrids.

In recent years, hydrogen has become a popular renewable energy carrier and has gained great attention from enterprises and governments. Saatloo et al. [123] proposed a sustainable energy platform integrating plugin electric vehicles and fuel cell electric vehicles with hydrogen as energy carriers. Furthermore, a decentralized model deployed in a mobile edge computing system is implemented for this integrated hydrogen microgrid to interact in a local energy market. According to the experiment results, the proposed platform can reduce the total cost.

In summary, this section focuses on nine primary topics in edge computing-enabled smart grids, as shown in Table 3. Power grid distribution monitoring is one of the most important research topics aimed at handling the geographical diversity in renewable energy areas. With the development of the smart grid, smart meters play a crucial role in smart power systems. Research on smart grid detection can provide a safer and more stable power supply. The advanced metering system is another significant component of the smart grid, with several applications discussed in this subsection. Furthermore, anomaly and fault detection have been receiving increasing attention from

the smart grid community recently. Therefore, its subsection includes three popular methods of anomaly detection. The definition and benefits of SE are discussed, and two applications focused on different topics are described in its subsection. Finally, energy storage, resource management, and cyber security are emerging topics associated with grid edge. Exploring the use of edge computing technology in these areas helps enhance the resilience and reliability of the power grid. References in this section are summarized in Table 3 by research topics and listed in Table 4 by detailed settings in edge computing architecture.

Table 3. Reference Table of Edge Computing in Smart Grids.

Research Topics	References
Power Grid Distribution Monitoring	[91–94]
Smart Meters Management	[95–97,100]
Data Collection and Analysis	[101,102]
Anomaly Detection	[103–107]
Measurement Placement	[108,109]
State Estimation	[112,113]
Energy Storage	[114]
Resource Management	[115–117]
Security of Grid Edge Management System	[118,119]
Renewable Energy Forecasting	[120–123]

Table 4. Table of Edge Computing Architecture Detailed Settings in Smart Grids.

References	Edge Nodes	Edge Servers
[91]	IoT Devices for monitoring the smart grids	Wi-Fi access points or 5G base stations
[93]	The sensors installed on the tower and the wires	Edge computing nodes
[92,94–96,105]	Smart information devices such as smart meters	Concentrators
[97]	Smart meters	Long Range (LoRa) nodes
[101,106]	Smart meters	Edge transformers
[109,112]	Power Quality Meter (PQM) and Phasor Measurement Unit (PMU)	Co-located embedded personal computer (ePC)
[113]	Intelligent electronic devices (IEDs)	The IEDs that are elected as leader
[116]	Distributed energy resources (DERs) at grid edge	Edge of Network Grid Optimization (ENGO) devices
[117,119]	Distributed energy resources (DERs)	DER clients

5. Discussion and Future Opportunities

The major objective of this review paper is to comprehensively summarize and study edge computing and its advantages that can benefit various industries, especially the energy industry. In Sections 2 and 3, edge computing architectures and relative technologies are explored. The practical examples in Sections 2 and 3 demonstrated that edge computing can solve various issues by modifying specific edge computing frameworks based on basic edge computing architectures. These examples can also prove that edge computing can be used in a wide range of fields, such as smart cities and smart health. In the future, edge computing can contribute to more traditional fields and help with digital transformation. In Section 4, various edge computing technologies in the smart grid edge are discussed and illustrate that with the development of the smart grids and grid edge, the usage of distributed smart devices and energy resources is increasing. Edge computing can be an

ideal solution to fulfill different requirements in the energy industry, such as forecasting the generation of electricity with renewable energy resources. Figure 6 also illustrates that edge computing has become more and more important for energy systems and has been widely discussed in recent years.
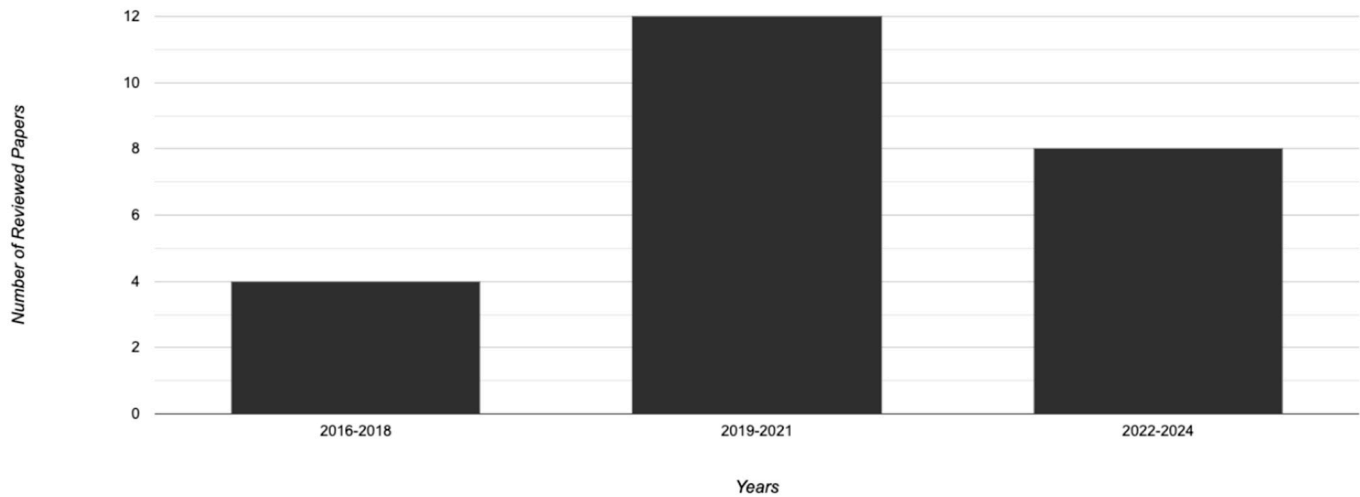

Figure 6. The number of reviewed papers over the years.

The emergence of the latest technologies has also proved that there are still numerous opportunities and topics to explore. In this section, we discuss several future opportunities for edge computing at the grid edge, including grid edge intelligence, 5G-based grid edge application, and grid edge workflow management.

5.1. Grid Edge Intelligence

At present, machine learning and AI are popular topics. As is well known, machine learning is a subset of AI and is a highly efficient approach for forecasting and decision-making. For power system management, it is important to keep the system operating stably and ensure grid resiliency. Machine learning, as a highly successful mathematical method, has great potential to satisfy these requirements well.

However, to pursue higher accuracy with machine learning models, a large amount of training and verification is required. Three general methods to resolve this conflict are improving the hardware of edge devices, optimizing machine learning models, and partitioning the models deployed on the end devices at the grid edge. For hardware improvement, the basic method is to add chips that can accelerate the training speed into the edge devices. Multi-core processing systems, multiprocessors, or even graphics processing units (GPUs) can be used in edge devices to accelerate the training speed. For partitioning the models on the edge devices, the independent model can be deployed in all edge devices. Another architecture is where edge devices cooperate with local edge servers to handle data processing and model training. High-performance computing (HPC) can also be introduced into edge intelligence and offer opportunities [124]. HPC is an ideal tool that can support real-time processing of vast datasets. Furthermore, this computational strength enables edge devices and edge servers to run scalable and complex machine learning algorithms. Although most systems and compilers running on smart devices or edge servers can provide parallel processing, the machine learning algorithms that can be executed in parallel still need to be developed with HPC technologies. With the integration between HPC and machine learning, the devices at the grid edge can complete more complex tasks, such as data preprocessing and model training.

With the development of modern power systems and energy resources, the power grid infrastructure encounters more and more uncertainties, such as erratic load [125]. It is important for algorithms used in power systems to deal with massive real-time uncertain variables. The power system is a huge and complex system with a large

number of nonlinear variables and uncertainties. Machine learning techniques can be used to propose models for uncertainty quantification. For example, machine learning regressions are one of the effective methods contributing to the development of models for uncertainty quantification.

There are also many other opportunities for machine learning to integrate into the grid edge. Implementing machine learning or deep learning-based fault detection in embedded edge devices can significantly augment the reliability of power systems. Cybersecurity of the grid edge has arisen due to the sensitive data stored and transmitted at the edge. Machine learning and AI can benefit the identifying and responding to potential threats.

5.2. 5G-Based Grid Edge Application

5G technologies are evolving rapidly and provide great opportunities for the development of edge computing. They allow for low delay, large bandwidth, and high-capacity communication. These advantages can benefit the power industry by efficiently connecting a vast number of smart edge devices. Additionally, 5G helps to establish reliable and accurate real-time control in smart grids. 5G is vital for solving problems in traditional power grids and extending the scale of DERs.

Although 5G brings opportunities to the traditional power industry, it also raises challenges. One of the most urgent problems to be solved is the rapid growth of data volume. The combination of 5G and edge computing is an ideal approach to balance the computational and data transmission burden. However, this also brings about a series of new challenges, such as data storage and security problems in edge devices. Furthermore, 5G-based edge computing can support faster fault detection, recovery, and real-time operations.

5.3. Grid Edge Workflow Management

Managing and optimizing operations at the edge of the power grid becomes more challenging with the increasing data volume and complexity. An efficient grid edge workflow is required to ensure the functional operation of data collection, monitoring, processing, and analysis, as well as reliable and secure communication and interoperability among diverse devices. Implementing automated control mechanisms, utilizing advanced algorithms, and deploying best-fit edge computing architectures to facilitate the operation of edge devices at the grid edge will certainly be a focus of research to enhance edge computing applicability and efficiency in power system applications.

6. Conclusions

This paper provides a comprehensive review of edge computing from the aspects of basic concepts, architecture, communication, and popular technologies. Edge computing, as an emerging distributed computing paradigm, enables data processing and computing at the edge of the network, close to the customer side. Three popular edge computing architectures are introduced: MAEC, which operates distributed computing tasks on the edge devices at the grid edge; Cloudlet computing, which features a Cloudlet layer between the cloud center and the edge devices, where Cloudlets perform as small edge servers to handle lightweight computing tasks; and fog computing, which includes a fog layer comprised of numerous fog nodes. The state-of-the-art technologies used in edge computing are comprehensively introduced. Various applications discussed demonstrate that edge computing has become a crucial technology across various fields.

This paper also explores a wide range of power applications that utilize edge computing technologies, effectively demonstrating how these technologies are enhancing power system management. As the number of smart devices in power grids grows, along with the increasing demands for speed and security, edge computing is expected to be deployed in increasingly diverse scenarios, providing substantial benefits.

Finally, the paper discusses several future opportunities related to emerging techniques as an extension of the review.

The articles mentioned in this review paper are all extracted from Google Scholar. The selection criteria are as follows: The search terms are closely related to the topics discussed in every subsection; The summarized works should be published in recent years; The papers should clearly describe the usage of edge computing.

This review paper serves as a reference to researchers interested in edge computing to comprehend the fundamental knowledge, learn about the popular applications, and advance research in power systems.

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References

1. Gong, C.; Liu, J.; Zhang, Q.; Chen, H.; Gong, Z. The Characteristics of Cloud Computing. In Proceedings of the 2010 39th International Conference on Parallel Processing Workshops, San Diego, CA, USA, 13–16 September 2010; pp. 275–279.
2. Google and IBM Announce University Initiative to Address Internet-Scale Computing Challenges. Available online: https://sites.google.com/site/cloudcomplab/home/google-and-ibm-announce-university-initiative-to-address-internet-scale-computing-challenges-1 (accessed on 27 May 2024).
3. Dillon, T.; Wu, C.; Chang, E. Cloud Computing: Issues and Challenges. In Proceedings of the 2010 24th IEEE International Conference on Advanced Information Networking and Applications, Perth, WA, Australia, 20–23 April 2010; pp. 27–33.
4. Cao, K.; Liu, Y.; Meng, G.; Sun, Q. An Overview on Edge Computing Research. *IEEE Access* **2020**, *8*, 85714–85728. [CrossRef]
5. The Internet of Things: How the Next Evolution of the Internet Is Changing Everything. Available online: https://www.cisco.com/c/dam/en_us/about/ac79/docs/innov/IoT_IBSG_0411FINAL.pdf (accessed on 27 May 2024).
6. Mach, P.; Becvar, Z. Mobile Edge Computing: A Survey on Architecture and Computation Offloading. *IEEE Commun. Surv. Tutor.* **2017**, *19*, 1628–1656. [CrossRef]
7. Internet of Things and Data Placement. Available online: https://infohub.delltechnologies.com/en-us/l/edge-to-core-and-the-internet-of-things-2/internet-of-things-and-data-placement/ (accessed on 27 May 2024).
8. Menon, V.G.; Jacob, S.; Joseph, S.; Sehdev, P.; Khosravi, M.R.; Al-Turjman, F. An IoT-Enabled Intelligent Automobile System for Smart Cities. *Internet Things* **2022**, *18*, 100213. [CrossRef]
9. Gao, Y.; Guan, H.; Qi, Z.; Song, T.; Huan, F.; Liu, L. Service Level Agreement Based Energy-Efficient Resource Management in Cloud Data Centers. *Comput. Electr. Eng.* **2014**, *40*, 1621–1633. [CrossRef]
10. Chen, Y.; Wang, L.; Fan, X.; Wang, D.; Ogle, J. A 5G Enabled Adaptive Computing Workflow for Greener Power Grid. In Proceedings of the 2023 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, USA, 16–19 January 2023; pp. 1–5.
11. Ishtiaq, M.; Saeed, N.; Khan, M.A. Edge Computing in IoT: A 6G Perspective. *arXiv* **2021**, arXiv:2111.08943.
12. Carvalho, G.; Cabral, B.; Pereira, V.; Bernardino, J. Edge Computing: Current Trends, Research Challenges and Future Directions. *Computing* **2021**, *103*, 993–1023. [CrossRef]
13. Hassan, N.; Yau, K.-L.A.; Wu, C. Edge Computing in 5G: A Review. *IEEE Access* **2019**, *7*, 127276–127289. [CrossRef]
14. Li, X.; Wang, Z. A Cloud-Edge Computing Method for Integrated Electricity-Gas System Dispatch. *Processes* **2023**, *11*, 2299. [CrossRef]
15. Mercury Energy Uses Cloud Computing Successfully | Fronde Blog. Available online: https://www.fronde.com/post/mercury-energy-uses-cloud-computing-successfully (accessed on 18 June 2024).
16. Mobile-Edge Computing—Introductory Technical. Available online: https://networkbuilders.intel.com/solutionslibrary/mobile-edge-computing-introductory-technical (accessed on 27 May 2024).
17. Ali, B.; Gregory, M.A.; Li, S. Multi-Access Edge Computing Architecture, Data Security and Privacy: A Review. *IEEE Access* **2021**, *9*, 18706–18721. [CrossRef]
18. Multi-Access Edge Computing (MEC); Framework and Reference Architecture. Available online: https://www.etsi.org/deliver/etsi_gs/MEC/001_099/003/03.01.01_60/gs_mec003v030101p.pdf (accessed on 27 May 2024).
19. Sabella, D.; Vaillant, A.; Kuure, P.; Rauschenbach, U.; Giust, F. Mobile-Edge Computing Architecture: The Role of MEC in the Internet of Things. *IEEE Consum. Electron. Mag.* **2016**, *5*, 84–91. [CrossRef]
20. Nastic, S.; Rausch, T.; Scekic, O.; Dustdar, S.; Gusev, M.; Koteska, B.; Kostoska, M.; Jakimovski, B.; Ristov, S.; Prodan, R. A Serverless Real-Time Data Analytics Platform for Edge Computing. *IEEE Internet Comput.* **2017**, *21*, 64–71. [CrossRef]

21. Stantchev, V.; Barnawi, A.; Ghulam Muhammad, S.; Schubert, J.; Tamm, G. Smart Items, Fog and Cloud Computing as Enablers of Servitization in Healthcare. *Sens. Transducers* **2015**, *185*, 121–128.

22. Sneps-Sneppe, M.; Namiot, D. On Mobile Cloud for Smart City Applications. *arXiv* **2016**, arXiv:1605.02886.

23. Sapienza, M.; Guardo, E.; Cavallo, M.; La Torre, G.; Leombruno, G.; Tomarchio, O. Solving Critical Events through Mobile Edge Computing: An Approach for Smart Cities. In Proceedings of the 2016 IEEE International Conference on Smart Computing (SMARTCOMP), St. Louis, MO, USA, 18–20 May 2016; pp. 1–5.

24. Hong, K.; Lillethun, D.; Ramachandran, U.; Ottenwälder, B.; Koldehofe, B. Mobile Fog: A Programming Model for Large-Scale Applications on the Internet of Things. In Proceedings of the Second ACM SIGCOMM Workshop on Mobile Cloud Computing, Hong Kong, China, 16 August 2013; Association for Computing Machinery: New York, NY, USA, 2013; pp. 15–20.

25. Computer Technology Increasingly Aids Traffic Management. Available online: https://www.itsinternational.com/its4/its8/feature/computer-technology-increasingly-aids-traffic-management (accessed on 27 May 2024).

26. Datta, S.K.; Bonnet, C.; Haerri, J. Fog Computing Architecture to Enable Consumer Centric Internet of Things Services. In Proceedings of the 2015 International Symposium on Consumer Electronics (ISCE), Madrid, Spain, 24–26 June 2015; pp. 1–2.

27. Satyanarayanan, M.; Bahl, P.; Caceres, R.; Davies, N. The Case for VM-Based Cloudlets in Mobile Computing. *IEEE Pervasive Comput.* **2009**, *8*, 14–23. [CrossRef]

28. Dastjerdi, A.V.; Gupta, H.; Calheiros, R.N.; Ghosh, S.K.; Buyya, R. Fog Computing: Principles, Architectures, and Applications. In *Internet of Things*; Elsevier: Amsterdam, The Netherlands, 2016; pp. 61–75.

29. Kotevska, O.; Lbath, A.; Bouzefrane, S. Toward a Framework in Cloudlet-Based Architecture for a Real-Time Predictive Model. In Proceedings of the 2015 IEEE 12th Intl Conf on Ubiquitous Intelligence and Computing and 2015 IEEE 12th Intl Conf on Autonomic and Trusted Computing and 2015 IEEE 15th Intl Conf on Scalable Computing and Communications and Its Associated Workshops (UIC-ATC-ScalCom), Beijing, China, 10–14 August 2015; pp. 1016–1021.

30. Bou Abdo, J.; Demerjian, J. Evaluation of Mobile Cloud Architectures. *Pervasive Mob. Comput.* **2017**, *39*, 284–303. [CrossRef]

31. Soyata, T.; Muraleedharan, R.; Funai, C.; Kwon, M.; Heinzelman, W. Cloud-Vision: Real-Time Face Recognition Using a Mobile-Cloudlet-Cloud Acceleration Architecture. In Proceedings of the 2012 IEEE Symposium on Computers and Communications (ISCC), Cappadocia, Turkey, 1–4 July 2012; pp. 000059–000066.

32. Chandavale, A.A.; Gade, A.J. Cloudlet Based Healthcare and Medical Knowledge Extraction System for Medical Big Data. *Int. J. Comput. Sci. Inf. Secur. (IJCSIS)* **2018**, *16*, 146–152.

33. Khanh, T.T.; Nguyen, V.; Pham, X.-Q.; Huh, E.-N. Wi-Fi Indoor Positioning and Navigation: A Cloudlet-Based Cloud Computing Approach. *Hum.-Centric Comput. Inf. Sci.* **2020**, *10*, 32. [CrossRef]

34. Sahkhar, L.; Balabantaray, B.K.; Panda, S.K. Mobility-Enhanced Delay-Aware Cloudlet Movement and Placement Using Cluster-Based Technique in a Smart Healthcare Platform. *Cluster Comput.* **2024**. [CrossRef]

35. Hughes, R.; Muheidat, F.; Lee, M.; Tawalbeh, L.A. Floor Based Sensors Walk Identification System Using Dynamic Time Warping with Cloudlet Support. In Proceedings of the 2019 IEEE 13th International Conference on Semantic Computing (ICSC), Newport Beach, CA, USA, 30 January–1 February 2019; pp. 440–444.

36. Otomo, M.; Sato, G.; Shibata, Y. In-Vehicle Cloudlet Computing Based on Delay Tolerant Network Protocol for Disaster Information System. In *Advances on Broad-Band Wireless Computing, Communication and Applications: Proceedings of the 11th International Conference On Broad-Band Wireless Computing, Communication and Applications (BWCCA–2016), Korea, 5–7 November 2016*; Springer: Cham, Switzerland, 2017; pp. 255–266.

37. OpenFog Reference Architecture for Fog Computing. Available online: https://www.iiconsortium.org/pdf/OpenFog_Reference_Architecture_2_09_17.pdf (accessed on 27 May 2024).

38. Mahmud, R.; Kotagiri, R.; Buyya, R. Fog Computing: A Taxonomy, Survey and Future Directions. In *Internet of Everything: Algorithms, Methodologies, Technologies and Perspectives*; Di Martino, B., Li, K.-C., Yang, L.T., Esposito, A., Eds.; Springer: Singapore, 2018; pp. 103–130, ISBN 978-981-10-5861-5.

39. Das, R.; Inuwa, M.M. A Review on Fog Computing: Issues, Characteristics, Challenges, and Potential Applications. *Telemat. Inform. Rep.* **2023**, *10*, 100049. [CrossRef]

40. Sabireen, H.; Neelanarayanan, V. A Review on Fog Computing: Architecture, Fog with IoT, Algorithms and Research Challenges. *ICT Express* **2021**, *7*, 162–176. [CrossRef]

41. Yi, S.; Hao, Z.; Qin, Z.; Li, Q. Fog Computing: Platform and Applications. In Proceedings of the 2015 Third IEEE workshop on hot topics in web systems and technologies (HotWeb), Washington, DC, USA 12–13 November 2015; IEEE: Piscataway, NJ, USA, 2015; pp. 73–78.

42. Ai, Y.; Peng, M.; Zhang, K. Edge Computing Technologies for Internet of Things: A Primer. *Digit. Commun. Netw.* **2018**, *4*, 77–86. [CrossRef]

43. Hu, P.; Dhelim, S.; Ning, H.; Qiu, T. Survey on Fog Computing: Architecture, Key Technologies, Applications and Open Issues. *J. Netw. Comput. Appl.* **2017**, *98*, 27–42. [CrossRef]

44. Alli, A.A.; Alam, M.M. The Fog Cloud of Things: A Survey on Concepts, Architecture, Standards, Tools, and Applications. *Internet Things* **2020**, *9*, 100177. [CrossRef]

45. Cao, Y.; Chen, S.; Hou, P.; Brown, D. FAST: A Fog Computing Assisted Distributed Analytics System to Monitor Fall for Stroke Mitigation. In Proceedings of the 2015 IEEE International Conference on Networking, Architecture and Storage (NAS), Boston, MA, USA, 6–7 August 2015; IEEE: Piscataway, NJ, USA, 2015; pp. 2–11.

46. Vilela, P.H.; Rodrigues, J.J.P.C.; Solic, P.; Saleem, K.; Furtado, V. Performance Evaluation of a Fog-Assisted IoT Solution for e-Health Applications. *Future Gener. Comput. Syst.* **2019**, *97*, 379–386. [CrossRef]

47. Azimi, I.; Anzanpour, A.; Rahmani, A.M.; Pahikkala, T.; Levorato, M.; Liljeberg, P.; Dutt, N. HiCH: Hierarchical Fog-Assisted Computing Architecture for Healthcare IoT. *ACM Trans. Embed. Comput. Syst.* **2017**, *16*, 174:1–174:20. [CrossRef]

48. Monteiro, A.; Dubey, H.; Mahler, L.; Yang, Q.; Mankodiya, K. Fit: A Fog Computing Device for Speech Tele-Treatments. In Proceedings of the 2016 IEEE International Conference on Smart Computing (SMARTCOMP), St. Louis, MO, USA, 18–20 May 2016; pp. 1–3.

49. Thakur, A.; Malekian, R. Fog Computing for Detecting Vehicular Congestion, an Internet of Vehicles Based Approach: A Review. *IEEE Intell. Transp. Syst. Mag.* **2019**, *11*, 8–16. [CrossRef]

50. Pereira, J.; Ricardo, L.; Luís, M.; Senna, C.; Sargento, S. Assessing the Reliability of Fog Computing for Smart Mobility Applications in VANETs. *Future Gener. Comput. Syst.* **2019**, *94*, 317–332. [CrossRef]

51. Serdaroglu, K.C.; Baydere, Ş.; Saovapakhiran, B.; Charnsripinyo, C. Location Aware Fog Computing Based Air Quality Monitoring System. In Proceedings of the 2023 International Conference on Smart Applications, Communications and Networking (SmartNets), Istanbul, Turkiye, 25–27 July 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 1–6.

52. Aliyu, F.; Abdeen, M.A.R.; Sheltami, T.; Alfraidi, T.; Ahmed, M.H. Fog Computing-Assisted Path Planning for Smart Shopping. *Multimed. Tools Appl.* **2023**, *82*, 38827–38852. [CrossRef] [PubMed]

53. Yi, S.; Hao, Z.; Zhang, Q.; Zhang, Q.; Shi, W.; Li, Q. Lavea: Latency-Aware Video Analytics on Edge Computing Platform. In Proceedings of the Second ACM/IEEE Symposium on Edge Computing, San Jose, CA, USA, 12–14 October 2017; pp. 1–13.

54. Lin, Y.; Shen, H. CloudFog: Leveraging Fog to Extend Cloud Gaming for Thin-Client MMOG with High Quality of Service. *IEEE Trans. Parallel Distrib. Syst.* **2016**, *28*, 431–445. [CrossRef]

55. Rezgui, J.; Soldevila, E.; Mokraoui, A. LRIMa City: A Fog-Computing-Based Smart City with Integrated Self-Driving Cars. In Proceedings of the 2023 International Symposium on Networks, Computers and Communications (ISNCC), Doha, Qatar, 23–26 October 2023; pp. 1–7.

56. Awaisi, K.S.; Abbas, A.; Zareei, M.; Khattak, H.A.; Shahid Khan, M.U.; Ali, M.; Ud Din, I.; Shah, S. Towards a Fog Enabled Efficient Car Parking Architecture. *IEEE Access* **2019**, *7*, 159100–159111. [CrossRef]

57. Yu, S.; Wang, X.; Langar, R. Computation Offloading for Mobile Edge Computing: A Deep Learning Approach. In Proceedings of the 2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communica-tions (PIMRC), Montreal, QC, Canada, 8–13 October 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–6.

58. Zhang, K.; Mao, Y.; Leng, S.; Vinel, A.; Zhang, Y. Delay Constrained Offloading for Mobile Edge Computing in Cloud-Enabled Vehicular Networks. In Proceedings of the 2016 8th International Workshop on Resilient Networks Design and Modeling (RNDM), Halmstad, Sweden, 13–15 September 2016; pp. 288–294.

59. Zhang, J.; Guo, H.; Liu, J.; Zhang, Y. Task Offloading in Vehicular Edge Computing Networks: A Load-Balancing Solution. *IEEE Trans. Veh. Technol.* **2020**, *69*, 2092–2104. [CrossRef]

60. Hung, C.-C.; Ananthanarayanan, G.; Bodik, P.; Golubchik, L.; Yu, M.; Bahl, P.; Philipose, M. VideoEdge: Processing Camera Streams Using Hierarchical Clusters. In Proceedings of the 2018 IEEE/ACM Symposium on Edge Computing (SEC), Seattle, WA, USA, 25–27 October 2018; pp. 115–131.

61. Xu, X.; Wu, Q.; Qi, L.; Dou, W.; Tsai, S.-B.; Bhuiyan, M.Z.A. Trust-Aware Service Offloading for Video Surveillance in Edge Computing Enabled Internet of Vehicles. *IEEE Trans. Intell. Transp. Syst.* **2021**, *22*, 1787–1796. [CrossRef]

62. Yu, G.; Chai, T.; Luo, X. Multiobjective Production Planning Optimization Using Hybrid Evolutionary Algorithms for Mineral Processing. *IEEE Trans. Evol. Comput.* **2011**, *15*, 487–514. [CrossRef]

63. Fan, Q.; Ansari, N. On Cost Aware Cloudlet Placement for Mobile Edge Computing. *IEEE/CAA J. Autom. Sin.* **2019**, *6*, 926–937. [CrossRef]

64. Santoyo-González, A.; Cervelló-Pastor, C. Network-Aware Placement Optimization for Edge Computing Infrastructure Under 5G. *IEEE Access* **2020**, *8*, 56015–56028. [CrossRef]

65. Jin, J.; Li, Y.; Luo, J. Cooperative Storage by Exploiting Graph-Based Data Placement Algorithm for Edge Computing Environment. *Concurr. Comput. Pract. Exp.* **2018**, *30*, e4914. [CrossRef]

66. Plachy, J.; Becvar, Z.; Strinati, E.C. Dynamic Resource Allocation Exploiting Mobility Prediction in Mobile Edge Computing. In Proceedings of the 2016 IEEE 27th Annual International Symposium on Personal, Indoor, and Mobile Radio Communica-tions (PIMRC), Valencia, Spain, 4–8 September 2016; pp. 1–6.

67. Abdelwahab, S.; Hamdaoui, B.; Guizani, M.; Znati, T. Replisom: Disciplined Tiny Memory Replication for Massive IoT Devices in LTE Edge Cloud. *IEEE Internet Things J.* **2016**, *3*, 327–338. [CrossRef]

68. Kumar, N.; Zeadally, S.; Rodrigues, J.J.P.C. Vehicular Delay-Tolerant Networks for Smart Grid Data Management Using Mobile Edge Computing. *IEEE Commun. Mag.* **2016**, *54*, 60–66. [CrossRef]

69. Wen, J.; Ren, C.; Sangaiah, A.K. Energy-Efficient Device-to-Device Edge Computing Network: An Approach Offloading Both Traffic and Computation. *IEEE Commun. Mag.* **2018**, *56*, 96–102. [CrossRef]

70. Li, C.; Tang, J.; Tang, H.; Luo, Y. Collaborative Cache Allocation and Task Scheduling for Data-Intensive Applications in Edge Computing Environment. *Future Gener. Comput. Syst.* **2019**, *95*, 249–264. [CrossRef]

71. Zhang, K.; Leng, S.; He, Y.; Maharjan, S.; Zhang, Y. Cooperative Content Caching in 5G Networks with Mobile Edge Computing. *IEEE Wirel. Commun.* **2018**, *25*, 80–87. [CrossRef]

72. Xia, X.; Chen, F.; He, Q.; Grundy, J.; Abdelrazek, M.; Jin, H. Online Collaborative Data Caching in Edge Computing. *IEEE Trans. Parallel Distrib. Syst.* **2021**, *32*, 281–294. [CrossRef]

73. Zhang, J.; Hu, X.; Ning, Z.; Ngai, E.C.-H.; Zhou, L.; Wei, J.; Cheng, J.; Hu, B. Energy-Latency Tradeoff for Energy-Aware Offloading in Mobile Edge Computing Networks. *IEEE Internet Things J.* **2018**, *5*, 2633–2645. [CrossRef]

74. Li, Y.; Wang, S. An Energy-Aware Edge Server Placement Algorithm in Mobile Edge Computing. In Proceedings of the 2018 IEEE International Conference on Edge Computing (EDGE), San Francisco, CA, USA, 2–7 July 2018; pp. 66–73.

75. Hao, Y.; Cao, J.; Wang, Q.; Du, J. Energy-Aware Scheduling in Edge Computing with a Clustering Method. *Future Gener. Comput. Syst.* **2021**, *117*, 259–272. [CrossRef]

76. Xing, J.; Dai, H.; Yu, Z. A Distributed Multi-Level Model with Dynamic Replacement for the Storage of Smart Edge Computing. *J. Syst. Archit.* **2018**, *83*, 1–11. [CrossRef]

77. Adeniran, A.B. Architecture Design and Optimization of Edge-Enabled Smart Grids. Master's Thesis, University of South Florida, Tampa, FL, USA, 2020.

78. Liu, Y.; Peng, Y.; Wang, B.; Yao, S.; Liu, Z. Review on Cyber-Physical Systems. *IEEE/CAA J. Autom. Sin.* **2017**, *4*, 27–40. [CrossRef]

79. Our Commitment to Smart Grid Technology—IEEE Smart Grid. Available online: https://smartgrid.ieee.org/about-ieee-smart-grid (accessed on 27 June 2024).

80. Supercharging the Electric Grid Edge for an Integrated Energy System. Available online: https://www.energy.gov/eere/supercharging-electric-grid-edge-integrated-energy-system (accessed on 29 May 2024).

81. Jamuna, H.G.; Hugar, S. Smarter Grid Embedded in an Internet of Things. *Int. J. Eng. Tech.* **2016**, *2*, 22–26.

82. Arcas, G.I.; Cioara, T.; Anghel, I.; Lazea, D.; Hangan, A. Edge Offloading in Smart Grid. *Smart Cities* **2024**, *7*, 680–711. [CrossRef]

83. 2023 IEEE PES Grid Edge Technologies: Session: Tutorial: The Grid Edge Is the Future, A Golden Future Date. Available online: https://s23.a2zinc.net/Clients/IEEE/IEEE23/Public/SessionDetails.aspx?%20FromPage=Sessions.aspx&SessionID=1879&SessionDateID=25 (accessed on 27 May 2024).

84. Digital Transformation at the Grid Edge. Available online: https://www.smart-energy.com/industry-sectors/smart-grid/digital-transformation-at-the-grid-edge/ (accessed on 27 May 2024).

85. Another $1.2 Billion Substation? No Thanks, Says Utility, We'll Find a Better Way. Available online: https://insideclimatenews.org/news/04042016/coned-brooklyn-queens-energy-demand-management-project-solar-fuel-cells-climate-change/ (accessed on 27 May 2024).

86. What to Expect from California Utilities' New Aggregated Demand Response Offerings. Available online: https://www.utilitydive.com/news/what-to-expect-from-california-utilities-new-aggregated-demand-response-of/412614/ (accessed on 27 May 2024).

87. Edge Computing Fuels a Sustainable Future for Energy. Available online: https://developer.nvidia.com/blog/edge-computing-fuels-a-sustainable-future-for-energy/ (accessed on 19 June 2024).

88. Noteworthy AI—Proactive Infrastructure Intelligence. Available online: https://www.noteworthy.ai/ (accessed on 19 June 2024).

89. Startup Surge: Utility Feels Power of Computer Vision to Track Its Lines. Available online: https://resources.nvidia.com/en-us-energy-utilities/power-utility-ai-edge (accessed on 19 June 2024).

90. Martin, S. Electrifying AI: Siemens Energy Taps NVIDIA Triton Inference Server for Power Plant Inspections, Autonomy. Available online: https://blogs.nvidia.com/blog/siemens-energy-taps-nvidia-triton-inference-server-for-power-plant-inspections-autonomy/ (accessed on 19 June 2024).

91. Huang, Y.; Lu, Y.; Wang, F.; Fan, X.; Liu, J.; Leung, V.C.M. An Edge Computing Framework for Real-Time Monitoring in Smart Grid. In Proceedings of the 2018 IEEE International Conference on Industrial Internet (ICII), Seattle, WA, USA, 21–23 October 2018; pp. 99–108.

92. Tom, R.J.; Sankaranarayanan, S.; de Albuquerque, V.H.C.; Rodrigues, J.J.P.C. Aggregator Based RPL for an IoT-Fog Based Power Distribution System with 6LoWPAN. *China Commun.* **2020**, *17*, 104–117. [CrossRef]

93. Sun, Y.; Li, X.; Liu, Y.; Hu, J. Edge Computing Terminal Equipment Planning Method for Real-Time Online Monitoring Service of Power Grid. In Proceedings of the 2019 IEEE 4th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), Chengdu, China, 20–22 December 2019; Volume 1, pp. 35–41.

94. Forcan, M.; Maksimović, M. Cloud-Fog-Based Approach for Smart Grid Monitoring. *Simul. Model. Pract. Theory* **2020**, *101*, 101988. [CrossRef]

95. Utomo, D.; Hsiung, P.-A. A Multitiered Solution for Anomaly Detection in Edge Computing for Smart Meters. *Sensors* **2020**, *20*, 5159. [CrossRef] [PubMed]

96. Liu, F.; Liang, C.; He, Q. Remote Malfunctional Smart Meter Detection in Edge Computing Environment. *IEEE Access* **2020**, *8*, 67436–67443. [CrossRef]

97. Kumari, P.; Mishra, R.; Gupta, H.P.; Dutta, T.; Das, S.K. An Energy Efficient Smart Metering System Using Edge Computing in LoRa Network. *IEEE Trans. Sustain. Comput.* **2022**, *7*, 786–798. [CrossRef]

98. Olivares-Rojas, J.C.; Reyes-Archundia, E.; Gutiérrez-Gnecchi, J.A.; Molina-Moreno, I.; Téllez-Anguiano, A.C.; Cerda-Jacobo, J. Smart Metering System Data Analytics Platform Using Multicore Edge Computing. *Int. J. Reconfigurable Embed. Syst.* **2021**, *10*, 11. [CrossRef]

99. NOBEL GRID. Available online: https://www.grupoetra.com/en/portfolio-item/nobel-grid/ (accessed on 29 May 2024).

100. Qin, C.; Srivastava, A.K.; Davies, K.L. Unbundling Smart Meter Services Through Spatiotemporal Decomposition Agents in DER-Rich Environment. *IEEE Trans. Ind. Inform.* **2022**, *18*, 666–676. [CrossRef]

101. Si, F.; Han, Y.; Wang, J.; Zhao, Q. Connectivity Verification in Distribution Systems Using Smart Meter Voltage Analytics: A Cloud-Edge Collaboration Approach. *IEEE Trans. Ind. Inform.* **2021**, *17*, 3929–3939. [CrossRef]

102. Sirojan, T.; Lu, S.; Phung, B.T.; Ambikairajah, E. Embedded Edge Computing for Real-Time Smart Meter Data Analytics. In Proceedings of the 2019 International Conference on Smart Energy Systems and Technologies (SEST), Porto, Portugal, 9–11 September 2019; pp. 1–5.

103. Cui, W.; Wang, H. Anomaly Detection and Visualization of School Electricity Consumption Data. In Proceedings of the 2017 IEEE 2nd International Conference on Big Data Analysis (ICBDA), Beijing, China, 10–12 March 2017; pp. 606–611.

104. da Silva, A.; Guarany, I.S.; Arruda, B.; Gurjão, E.C.; Freire, R.S. A Method for Anomaly Prediction in Power Consumption Using Long Short-Term Memory and Negative Selection. In Proceedings of the 2019 IEEE International Symposium on Circuits and Systems (ISCAS), Sapporo, Japan, 26–29 May 2019; pp. 1–5.

105. Liang, H.; Ye, C.; Zhou, Y.; Yang, H. Anomaly Detection Based on Edge Computing Framework for AMI. In Proceedings of the 2021 IEEE International Conference on Electrical Engineering and Mechatronics Technology (ICEEMT), Qingdao, China, 2–4 July 2021; pp. 385–390.

106. Zheng, Y.; Chen, F.; Yang, H.; Su, S. Edge Computing Based Electricity-Theft Detection of Low-Voltage Users. *Front. Energy Res.* **2022**, *10*, 892541. [CrossRef]

107. Jaiswal, R.; Chakravorty, A.; Rong, C. Distributed Fog Computing Architecture for Real-Time Anomaly Detection in Smart Meter Data. In Proceedings of the 2020 IEEE Sixth International Conference on Big Data Computing Service and Applications (BigDataService), Oxford, UK, 3–6 August 2020; pp. 1–8.

108. Zhao, Y.; Ye, H. Power System Low Delay Resource Scheduling Model Based on Edge Computing Node. *Sci. Rep.* **2023**, *13*, 14634. [CrossRef]

109. Sodin, D.; Rudež, U.; Mihelin, M.; Smolnikar, M.; Čampa, A. Advanced Edge-Cloud Computing Framework for Automated PMU-Based Fault Localization in Distribution Networks. *Appl. Sci.* **2021**, *11*, 3100. [CrossRef]

110. Ahmad, M. *Power System State Estimation*; Artech House: Norwood, MA, USA, 2013; ISBN 978-1-60807-511-9.

111. Larson, R.E.; Tinney, W.F.; Peschon, J. State Estimation in Power Systems Part I: Theory and Feasibility. *IEEE Trans. Power Appar. Syst.* **1970**, *PAS-89*, 345–352. [CrossRef]

112. Meloni, A.; Pegoraro, P.A.; Atzori, L.; Benigni, A.; Sulis, S. Cloud-Based IoT Solution for State Estimation in Smart Grids: Exploiting Virtualization and Edge-Intelligence Technologies. *Comput. Netw.* **2018**, *130*, 156–165. [CrossRef]

113. Kuraganti, C.K.; Robert, B.P.; Gurrala, G.; Puthuparambil, A.B.; Sundaresan, R. A Distributed Hierarchy Based Framework for Validating Edge Devices Performing State Estimation in a Power System. In Proceedings of the 2020 IEEE International Conference on Power Systems Technology (POWERCON), Bangalore, India, 14–16 September 2020; pp. 1–6.

114. Chuangpishit, S.; Katiraei, F.; Chalamala, B.; Novosel, D. Mobile Energy Storage Systems: A Grid-Edge Technology to Enhance Reliability and Resilience. *IEEE Power Energy Mag.* **2023**, *21*, 97–105. [CrossRef]

115. Zhang, Y.Y.C.; Feng, C.; Shaffery, P.; Yang, R. Grid Edge Visibility: Gaps and a Road Map. *IEEE Electrif. Mag.* **2022**, *10*, 10–19. [CrossRef]

116. Moghe, R.; Tholomier, D.; Divan, D. Distribution Grid Edge Control: Field Demonstrations. In Proceedings of the 2016 IEEE Power and Energy Society General Meeting (PESGM), Boston, MA, USA, 17–21 July 2016; pp. 1–5.

117. Zhang, Y.Y.C.; Spieler, M. Bringing Artificial Intelligence to the Grid Edge [Technology Leaders]. *IEEE Electrif. Mag.* **2022**, *10*, 6–9. [CrossRef]

118. Hafiz, F.; Ishchenko, D. Security Enhancement of Network Constraint Grid-Edge Energy Management System. In Proceedings of the 2022 IEEE Industry Applications Society Annual Meeting (IAS), Detroit, MI, USA, 9–14 October 2022; pp. 1–8.

119. Gao, X.; Ali, M.; Sun, W. A Risk Assessment Framework for Cyber-Physical Security in Distribution Grids with Grid-Edge DERs. *Energies* **2024**, *17*, 1587. [CrossRef]

120. Ait Abdelmoula, I.; Idrissi Kaitouni, S.; Lamrini, N.; Jbene, M.; Ghennioui, A.; Mehdary, A.; El Aroussi, M. Towards a Sustainable Edge Computing Framework for Condition Monitoring in Decentralized Photovoltaic Systems. *Heliyon* **2023**, *9*, e21475. [CrossRef] [PubMed]

121. Lv, L.; Wu, Z.; Zhang, L.; Gupta, B.B.; Tian, Z. An Edge-AI Based Forecasting Approach for Improving Smart Microgrid Efficiency. *IEEE Trans. Ind. Inform.* **2022**, *18*, 7946–7954. [CrossRef]

122. Nammouchi, A.; Aupke, P.; Kassler, A.; Theocharis, A.; Raffa, V.; Felice, M.D. Integration of AI, IoT and Edge-Computing for Smart Microgrid Energy Management. In Proceedings of the 2021 IEEE International Conference on Environment and Electrical Engineering and 2021 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe), Bari, Italy, 7–10 September 2021; pp. 1–6.

123. Saatloo, A.M.; Mehrabi, A.; Marzband, M.; Mirzaei, M.A.; Aslam, N. Local Energy Market Design for Power- and Hydrogen-Based Microgrids Considering a Hybrid Uncertainty Controlling Approach. *IEEE Trans. Sustain. Energy* **2024**, *15*, 398–413. [CrossRef]

124. Chen, Y.; Fan, X.; Huang, R.; Huang, Q.; Li, A.; Guddanti, K.P. *Artificial Intelligence/Machine Learning Technology in Power System Applications*; Pacific Northwest National Laboratory (PNNL): Richland, WA, USA, 2024.

125. Rahim, S.; Siano, P. A Survey and Comparison of Leading-Edge Uncertainty Handling Methods for Power Grid Modernization. *Expert Syst. Appl.* **2022**, *204*, 117590. [CrossRef]