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A Review Paper On Energy-Efficient Iot Networks Using AI-Based Edge Computing

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Abstract: The rapid proliferation of Internet of Things (IoT) devices in modern power systems has transformed the landscape of energy management, enabling real-time monitoring, predictive maintenance, and decentralized control. However, the exponential growth in data generation poses significant challenges for conventional cloud computing (CC) infrastructures, including high latency, bandwidth congestion, and security vulnerabilities. To address these limitations, emerging paradigms such as fog computing (FC) and edge computing (EC) offer localized processing closer to the data source, reducing latency and optimizing network resources. This review paper examines the integration of CC, FC, and EC within smart grid architectures, highlighting their technical advantages, implementation challenges, and contributions to enhancing system efficiency, resilience, and adaptability. Furthermore, the paper analyzes hierarchical EC architectures, including device, edge server, and cloud layers, and their role in enabling real-time energy management, fault detection, and adaptive control. The findings underscore the critical role of hybrid computing models in supporting large-scale, latency-sensitive, and data-intensive smart energy systems, while emphasizing the need for continued research in secure, scalable, and intelligent computational

Keywords: Smart Grids, Edge Computing, Cloud-Fog Integration

1 INTRODUCTION

The increasing demand for smart energy systems has driven a rapid expansion in the deployment and variety of Internet of Things (IoT)-based smart devices within power systems [1]. IoT technologies have emerged as key enablers of smart grids, providing real-time monitoring, predictive maintenance, and decentralized control capabilities that enhance the efficiency, resilience, and adaptability of modern energy systems [2]. However, the exponential growth of IoT devices has generated massive volumes of data, creating significant demands for high-bandwidth communication networks and robust data processing infrastructures. Early projections highlighted the scale of this growth: Cisco Internet Business Solutions Group (IBSG) anticipated approximately 25 billion connected devices by 2015 and 50 billion by 2020 [3].

In terms of data generation, the International Data Corporation (IDC) reported that in 2010, over 1 zettabyte of digital data was generated globally, and by 2012, daily data generation reached approximately 2.5 exabytes [4]. Dell Technologies further estimated that by 2025, the number of IoT devices worldwide would reach 41.6 billion, collectively generating 79.4 zettabytes of data [5]. This unprecedented surge underscores the urgent need for innovative solutions capable of handling large-scale data traffic while efficiently managing network resources.

The massive volume of data produced by IoT devices necessitates advanced big data analytics and processing capabilities. Cisco's 2018–2023 report emphasizes the critical need for innovative network architectures and data management frameworks to address the challenges posed by this data explosion [6]. To meet these demands, cloud computing (CC) emerged as a transformative technology, offering scalable, flexible, and distributed data management solutions. Introduced by IBM and Google in 2007, cloud computing provided methodologies for developing internet-scale applications without relying on on-premises infrastructure [7,8]. While CC enables centralized storage, access, and processing of vast datasets, it also introduces significant security and privacy challenges, particularly as providers host sensitive corporate and customer data [9,10].

The rapid expansion of IoT has highlighted the limitations of traditional cloud-centric architectures, particularly in latency-sensitive and real-time applications. Centralized cloud processing increases response times, intensifies bandwidth congestion, and raises privacy concerns. To address these limitations, fog computing (FC) emerged as an intermediate solution, offering localized storage and computation closer to the network edge [11]. However, while FC alleviates some latency and bandwidth issues, it remains insufficient for fully real-time, latency-critical applications [12]. To overcome these challenges, edge computing (EC) has been introduced, enabling data processing directly at the source. Unlike cloud computing, EC significantly reduces communication latency, minimizes bandwidth overhead, and improves responsiveness for time-sensitive tasks such as real-time monitoring, fault detection, and control in smart grid systems [13,14]. In addition, EC offers potential benefits for energy efficiency, network optimization, and enhanced security by limiting data transmission to central servers [15].
Existing literature explores various aspects of EC implementation in smart grids, though many studies focus on specific components or theoretical frameworks. For example, some works provide overviews of EC potential in smart grids but note that practical deployments remain limited [16].

Others analyze the hardware and software architecture of EC-cloud integrated systems but offer little insight into application scenarios [17]. Further studies examine IoT and edge-based smart grid architectures, integration with SCADA systems, and challenges such as scalability, security, and resilience, while highlighting key applications like power distribution monitoring, microgrids, and advanced metering [18,19]. Reviews on fog and edge computing categorize emerging research areas and communication techniques, analyzing both architectural developments and practical deployment strategies [20,21]. Collectively, these studies underscore the growing importance of EC in managing the data-intensive and latency-sensitive demands of modern smart energy systems, paving the way for more efficient, resilient, and adaptive power grid infrastructures.

2 LITERATURE REVIEW

2.1 Cloud Computing

2.1.1 Overview of Cloud Computing

Cloud computing (CC) represents a paradigm shift in the way computing resources are delivered, enabling on-demand access to storage, services, and applications via the Internet [22]. The National Institute of Standards and Technology (NIST) defines cloud computing as "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction" [23]. Different types of computing is shown in figure 1.

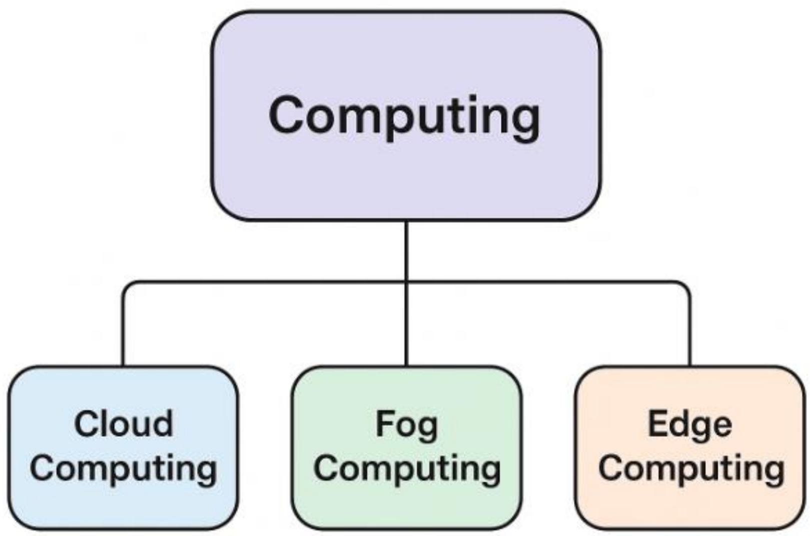

Figure 1 Different computing techniques

This model offers a highly scalable, flexible, and cost-effective framework for centralized data processing and management. In modern applications such as industrial automation, IoT-enabled infrastructures, and energy systems, CC plays a vital role in efficiently handling vast datasets through virtualization, multi-tenancy, and elastic resource allocation.

2.1.2 Advantages and Functional Capabilities

The core capabilities of cloud computing—such as scalability, elasticity, and centralized control—make it ideal for managing large-scale, data-intensive applications. Through dynamic provisioning of computational resources, cloud systems optimize operational efficiency and minimize capital expenditure. The ability to centralize data storage and computation enables enhanced data analytics, simulation, and decision support for complex systems, including energy management and smart grid control.

2.1.3 Challenges and Limitations

Despite its numerous benefits, cloud computing presents several technical and operational challenges. Its centralized architecture increases vulnerability to cyberattacks, such as data breaches, Distributed Denial-of-Service (DDoS) attacks, and exploitation of insecure APIs [24,9]. In IoT-integrated smart grids, these security issues pose risks to data privacy and system reliability.
Another significant limitation is **latency**—the physical distance between cloud servers and IoT devices introduces delays, making it difficult to meet the real-time response requirements of applications like frequency stabilization, power distribution control, and demand-response operations [25,26]. Although

heuristic optimization techniques such as Genetic Algorithms (GA) have been employed to minimize latency [27], these methods often fall short in time-critical scenarios.

2.1.4 Hybrid and Distributed Computing Solutions

To mitigate these challenges, hybrid architectures combining **fog computing (FC)** and **edge computing (EC)** have emerged. Fog computing introduces an intermediate layer between cloud servers and IoT devices, enabling pre-processing, data aggregation, and localized computation closer to data sources [28]. Edge computing extends this concept further by performing computations directly at the device or network edge, thereby minimizing communication delays and reducing bandwidth usage [13,14]. These distributed models improve system responsiveness, enhance energy efficiency, and support intelligent power management in smart grids.

2.1.5 Applications in Smart Grids

Cloud computing continues to play a central role in enabling **advanced smart grid functionalities**. Cloud infrastructures facilitate predictive maintenance, large-scale simulation, and dynamic energy optimization through self-healing mechanisms and centralized monitoring platforms [29]. By utilizing time-shared processing cores, multiple energy management algorithms can run concurrently without performance degradation [31].
Furthermore, cloud-based simulation environments allow operators to perform scenario analysis, forecast demand-generation patterns, and integrate renewable energy sources effectively [32,33]. CC also supports hybrid energy storage management by hosting predictive algorithms that extend battery lifespan and improve flexibility.

2.1.6 Integration of IoT and Cloud Computing

The convergence of **IoT and CC** amplifies the benefits of centralized computation. IoT devices continuously generate large volumes of heterogeneous data—such as voltage, current, frequency, and environmental parameters—that require rapid analysis for efficient energy management.
Frameworks like **CloudIoT** have been proposed to enhance interoperability, support real-time data analytics, and manage user demands within complex smart grid networks [34,35]. Research demonstrates that the integration of CC and IoT improves scalability, adaptability, and resilience, allowing predictive and proactive energy control across distributed systems [36,37].
However, challenges in big data handling, intermittent renewable generation, and cyber-physical security still persist. Continuous advancements in hybrid architectures are essential to achieve **fully autonomous, efficient, and resilient energy systems** of the future.

2.2 Edge Computing

2.2.1 Concept and Definition

Edge Computing (EC) is a distributed network paradigm that shifts computational processes closer to the data source, reducing latency, improving bandwidth utilization, and enhancing real-time decision-making [38]. Rather than relying solely on centralized cloud servers, EC allows data to be processed locally at IoT devices, user terminals, or edge servers.
As described in [12], EC is “a new computing model performed at the edge of the network,” combining computing and network resources positioned between the data source and the cloud data center. By placing storage and computation near mobile devices or sensors, EC delivers faster localized processing [39,40].

2.2.2 Architecture and Operational Mechanism

Technically, EC decentralizes both computation and storage by analyzing raw data locally before transmitting summarized information to the cloud [41]. This design extends cloud-like functionalities to the network's periphery, improving throughput and responsiveness [42].
A typical EC architecture comprises **three layers**:

1. **Device Layer** – Includes sensors, actuators, and intelligent electronic devices (IEDs) such as relays and analyzers deployed across power distribution networks. These devices acquire and preprocess electrical parameters like voltage and current.
2. **Edge Server Layer** – Acts as an intermediary that performs higher-level computations, such as fault detection, adaptive load management, and control operations, thereby reducing communication latency.
3. **Cloud Layer** – Handles large-scale data aggregation, machine learning-based analysis, and long-term storage for predictive and strategic decision-making.

2.2.3 Applications in Smart Grid Systems

In smart grids, EC is crucial for achieving **real-time monitoring**, **fault detection**, and **localized data analytics**. By processing data closer to where it is generated, EC minimizes communication delays, ensures faster control responses, and supports energy-efficient operations.
This layered architecture enables hybrid computing environments that combine the real-time benefits of EC with the extensive computational power of the cloud. As a result, systems achieve a balanced trade-off between **performance**, **scalability**, and **responsiveness** [21].

3 Conclusion

The review demonstrates that cloud computing, while indispensable for large-scale data management and advanced analytics in smart grids, faces inherent limitations in latency-sensitive applications. Fog and edge computing paradigms complement cloud infrastructure by providing localized computation and storage, thereby reducing response times, optimizing bandwidth, and enhancing operational efficiency. In smart grid applications, EC facilitates real-time monitoring, rapid fault detection, and adaptive energy management, bridging the gap between IoT data generation and centralized processing. Overall, hybrid computing architectures that integrate cloud, fog, and edge resources provide a balanced solution, combining scalability, reliability, and responsiveness to meet the evolving demands of modern power systems.

4 Future Scope

The future of smart energy systems lies in the development of intelligent, autonomous, and secure hybrid computing frameworks. Potential research directions include:

1. **Enhanced AI-driven Edge Analytics:** Integrating machine learning and predictive algorithms at the edge to enable autonomous decision-making and proactive maintenance.
2. **Energy-Efficient Architectures:** Designing edge and fog devices with low power consumption to optimize overall system energy efficiency.
3. **Cybersecurity and Privacy:** Developing robust encryption, access control, and anomaly detection mechanisms to safeguard sensitive energy and consumer data.
4. **Scalability and Interoperability:** Establishing standardized protocols to facilitate seamless integration of heterogeneous IoT devices across diverse smart grid infrastructures.
5. **Real-Time Hybrid Optimization:** Exploring hybrid cloud-edge-fog models that dynamically allocate computational tasks based on latency, bandwidth, and energy requirements for improved operational performance.

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