Distributed Computing in Smart Grids: A Survey

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Abstract

This survey systematically examines the integration of distributed computing technologies within smart grids, highlighting their roles in enhancing network security, precise measurements, energy management systems, grid optimization, and real-time data processing. The study underscores the importance of decentralized systems, such as cloud, edge, and fog computing, in addressing the complex and dynamic demands of modern smart grids. These frameworks optimize resource allocation and improve system performance, facilitating efficient energy distribution and consumption. The survey also explores network security challenges, emphasizing adaptive security algorithms and blockchain technology as robust solutions to potential threats. Precise measurements and real-time data processing are identified as crucial for accurate monitoring and control of energy resources, enabling timely decision-making and operational efficiency. Moreover, advanced optimization methods and algorithms significantly enhance the operational efficiency and sustainability of energy management systems. The evolution of distributed computing paradigms, including coded distributed computing, further enhances scalability and efficiency, providing a robust computational foundation for smart grids. Concluding, the survey affirms that integrating these technologies is vital for developing resilient and sustainable smart grid systems, capable of meeting the increasing demands of energy management and distribution networks, thereby contributing to the stability and sustainability of modern energy systems.

1 Introduction

1.1 Structure of the Survey

This survey systematically explores distributed computing within smart grids, beginning with an **Introduction** that highlights the intersection of distributed computing with network security, precise measurements, energy management systems, grid optimization, and real-time data processing. The **Background and Definitions** section provides foundational concepts, definitions, and the interconnections among these technologies within smart grids.

The section on **Distributed Computing in Smart Grids** emphasizes the integration and facilitation roles of distributed computing, underscoring the necessity for decentralized systems and the contributions of edge and fog computing. In the **Network Security in Smart Grids** section, we examine the critical importance of securing smart grid communications, detailing potential threats, vulnerabilities, and the implementation of adaptive security algorithms alongside decentralized management strategies.

Further, we explore **Precise Measurements and Real-Time Data Processing**, emphasizing their significance in accurately monitoring and controlling energy resources. The subsequent section analyzes , focusing on advanced optimization methods and distributed computing frameworks that enhance energy management efficiency. We discuss energy-aware algorithms across various layers of high-performance computing systems, including hardware and service layers, and their impact on reducing energy consumption. Additionally, we evaluate the effectiveness of Dynamic Voltage Frequency Scaling (DVFS) and resource provisioning techniques for MapReduce applications through

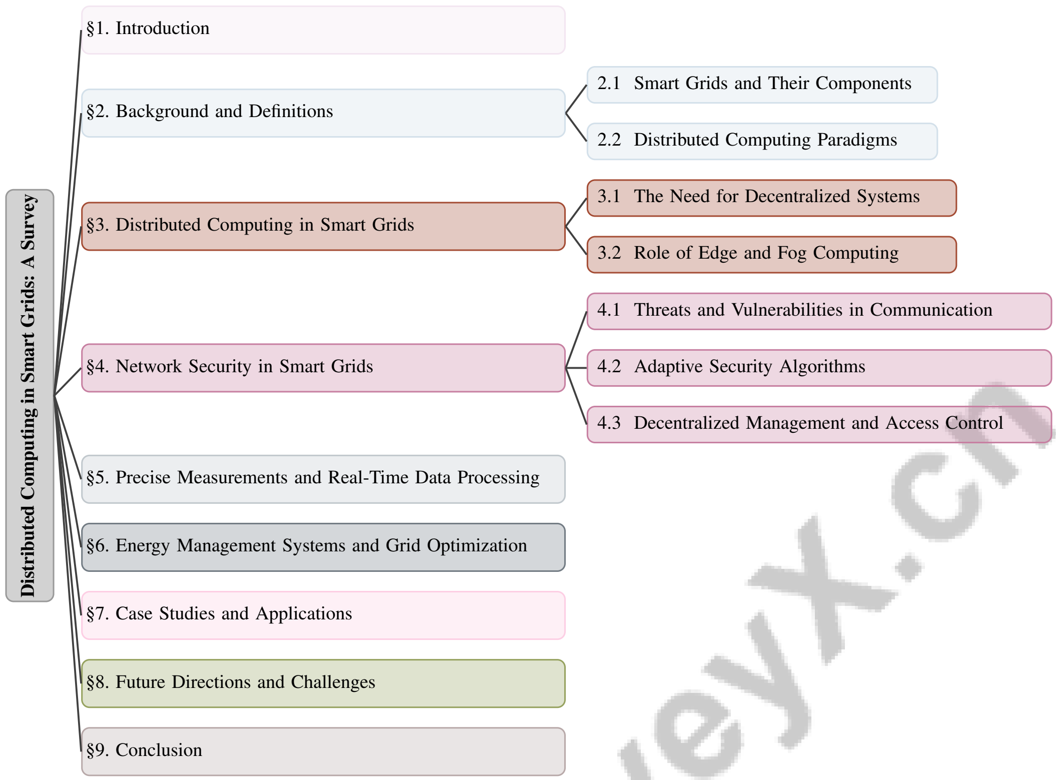

Figure 1: chapter structure

extensive simulations and real-world experiments. We also present a fully distributed Alternating Direction Method of Multipliers (ADMM) algorithm for economic dispatch, which adapts to real-time demand changes and enhances operational efficiency in power systems [1, 2, 3, 4, 5].

In the **Case Studies and Applications** section, we provide real-world examples that illustrate the practical implementation and benefits of these technologies in smart grids. The survey concludes with a thorough examination of , highlighting advancements in emerging technologies and trends in distributed computing, while addressing persistent issues related to scalability and efficiency. This section emphasizes the interplay between infrastructure providers and users, shaping the usage modalities of distributed systems, and offers insights into how evolving applications and infrastructures influence each other, along with the implications of current challenges in the context of cloud, grid, and distributed computing [6, 7, 1]. The survey concludes by summarizing key insights and reinforcing the significance of integrated technological frameworks in smart grids.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Smart Grids and Their Components

Smart grids represent the next generation of electrical systems, integrating advanced technologies to improve electricity distribution's efficiency, reliability, and sustainability. Core components include smart meters, advanced communication networks, and distributed energy resources. Smart meters enable real-time energy consumption data collection, allowing utilities to monitor usage patterns and optimize resource allocation [8]. The incorporation of distributed computing within smart grids enhances the management of these components, boosting grid reliability and resource utilization. Advanced communication networks, such as those utilizing GPS in distributed computing, are crucial for synchronizing and coordinating grid operations [9]. The absence of a unified Internet of Things (IoT) model highlights the complexity and diversity of devices and services in smart grid systems, necessitating robust management frameworks [10].

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Security is paramount in managing resources within cloud computing environments that support smart grid operations, with protection against unauthorized access and data breaches being essential for maintaining system integrity [11]. Blockchain-based federated learning (BCFL) architectures offer promising solutions for enhancing privacy and trust in distributed environments integral to smart grids [12]. These technologies optimize energy distribution and address security concerns, particularly in transactive energy systems where prosumer participation may risk privacy breaches and market manipulation [13]. Thus, smart grids provide a comprehensive framework leveraging cutting-edge technologies to revolutionize electricity network management and operation.

2.2 Distributed Computing Paradigms

Distributed computing paradigms are crucial to smart grid architectures, providing methodologies to address complex data processing and energy management demands. These paradigms—cloud computing, edge computing, grid computing, and peer-to-peer computing—each uniquely contribute to the optimization and scalability of smart grids [14]. Cloud computing offers a robust infrastructure for extensive data processing, essential for real-time analytics and decision-making [15]. However, traditional cloud models face challenges such as high energy consumption and inefficient resource utilization, affecting performance and reliability [16].

Edge computing addresses these limitations by decentralizing data processing, reducing latency, and enhancing response times by bringing computation closer to data sources. This approach is particularly beneficial for applications requiring real-time processing and low-latency communication, improving scalability and resilience [17]. Fog computing extends cloud services to the network edge, enhancing low-latency and real-time processing capabilities, essential for emerging IoT applications [18].

Grid computing focuses on optimal distributed computation across connected networks, reducing computational delay and cost, which is vital for smart grids where efficient data handling is imperative [19]. Consensus-based protocols for decentralized computation of network metrics bolster grid computing's support for smart grid applications [20]. Community cloud computing (C3) models leverage networked personal computers to create decentralized clouds, showcasing innovative distributed computing approaches [16].

Coded distributed computing (CDC) is significant for enabling distributed computation while mitigating straggler effects that can prolong completion times, particularly relevant in smart grid environments where timely data processing is critical [15]. The integration of distributed evolutionary computation (DEC) with parallel and distributed systems enhances efficiency and scalability, addressing centralized and distributed optimization challenges [18].

The evolution of these paradigms is driven by the increasing demand for efficient, reliable, and scalable solutions tailored to the unique challenges of smart grids, which require high-speed broadband networks, enhanced computing power, and advanced data management capabilities to optimize resource sharing across diverse applications [6, 1, 14]. As these paradigms evolve, they will play a critical role in advancing smart grid technologies, providing the computational foundation necessary for effective energy management and system optimization.

In recent years, the evolution of smart grid technology has underscored the importance of distributed computing systems. These systems not only enhance the operational efficiency of energy distribution but also align with the growing demand for scalable and secure solutions. Figure 2 illustrates the hierarchical structure of distributed computing in smart grids, focusing on the need for decentralized systems and the roles of edge and fog computing. This figure highlights key concepts such as scalability, efficiency, resource management, security, decentralization, and advanced analytics, all of which are essential for the efficient and reliable operation of smart grids. By examining these elements, we can better understand how they contribute to the overall resilience and adaptability of modern energy infrastructures.

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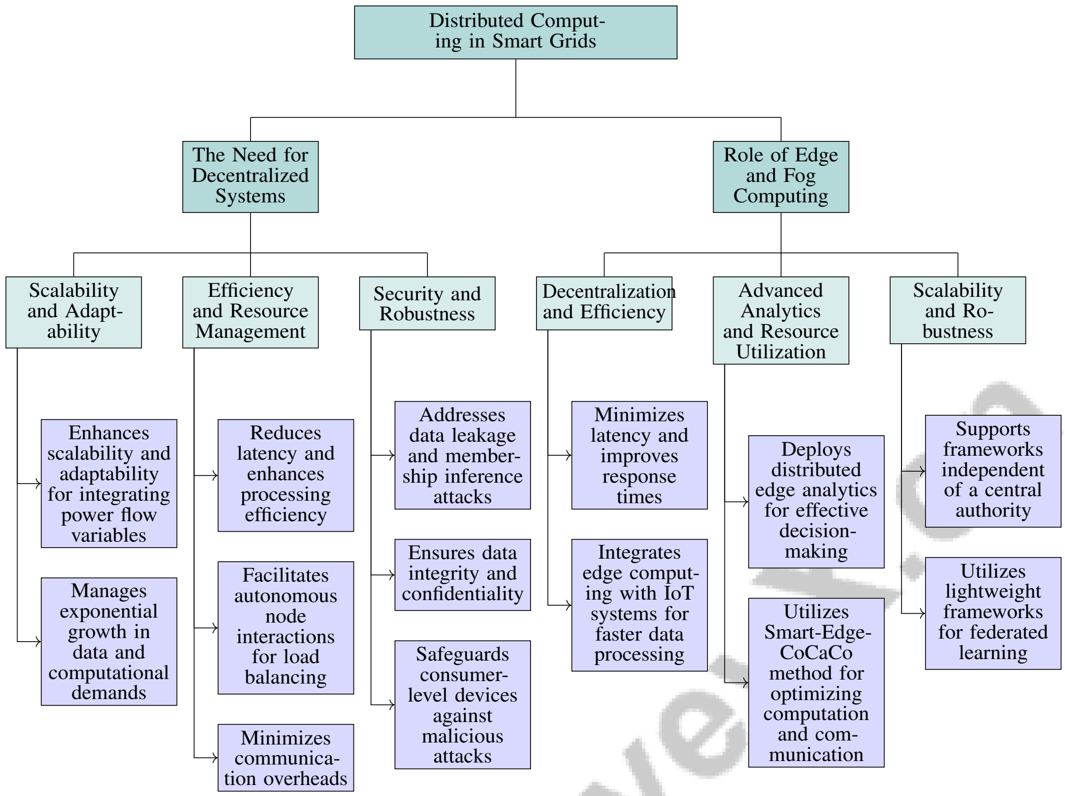

Figure 2: This figure illustrates the hierarchical structure of distributed computing in smart grids, focusing on the need for decentralized systems and the role of edge and fog computing. It highlights key concepts such as scalability, efficiency, resource management, security, decentralization, and advanced analytics that contribute to the efficient and reliable operation of smart grids.

3 Distributed Computing in Smart Grids

3.1 The Need for Decentralized Systems

Decentralized systems are fundamental to smart grid architecture, addressing the complexities and dynamic demands of these environments. They enhance scalability and adaptability, crucial for integrating additional power flow variables with minimal effort [16]. This adaptability is vital for managing the exponential growth in data and computational demands, enabling decentralized systems to efficiently tackle these challenges [17].

As illustrated in Figure 3, decentralized systems play key roles in smart grids by enhancing scalability and adaptability, improving efficiency and resource management, and ensuring security and reliability. In smart grids, variability in computation, communication, and storage capacities can lead to delays and failures, especially due to straggler nodes. Decentralized systems mitigate these issues by distributing computational tasks across multiple nodes, enhancing processing efficiency and reducing latency, essential for real-time data processing and decision-making in energy resource management [20, 18]. The lack of a centralized dispatcher complicates the dynamic organization of geographically distributed computers into clusters that respond to fluctuating resource demands. Decentralized systems facilitate autonomous node interactions, promoting efficient load balancing and resource management [21]. Moreover, integrating routing and processing decisions for both live data streams and static digital objects is crucial in smart grid applications [15].

High communication overheads during data shuffling present significant challenges in distributed settings [4]. Decentralized systems alleviate these overheads by minimizing extensive data exchanges, enhancing communication efficiency and overall system performance [2]. Additionally, the complexity of executing distributed applications across heterogeneous and dynamic resources is effectively managed by decentralized systems [22].

Security remains a paramount concern, as decentralized systems face challenges such as data leakage, membership inference attacks, and model poisoning, which threaten data integrity and confidentiality [20]. The increasing scale of distributed optimization problems necessitates robust security measures to safeguard consumer-level devices against potential malicious attacks [20]. Moreover, the requirement to transmit measurements from local nodes to a central node without overwhelming bandwidth while executing complex predictive models highlights the importance of decentralized approaches [20].

Current distributed computing platforms' intricate configuration and management often deter effective utilization of cloud resources [20]. Additionally, the trade-off between local data collection and collaborative data transfer under resource constraints complicates operations [20]. The nonhomogeneity of data across different sites further complicates the integration of results from separate analyses, leading to inefficiencies and information loss [20].

Decentralized systems are essential for the efficient and reliable operation of smart grids, providing the flexibility, adaptability, and robustness necessary to manage complex, dynamic, and heterogeneous environments. They address critical challenges such as high communication latency, inefficient resource utilization, and security concerns, thereby enhancing energy distribution and consumption efficiency. By facilitating the seamless integration and management of diverse components, including distributed energy resources and edge computing devices, decentralized systems ensure reliability and resiliency. Technologies like blockchain and consensus algorithms further optimize resource usage and improve responsiveness, contributing to a more resilient energy ecosystem [13, 23].

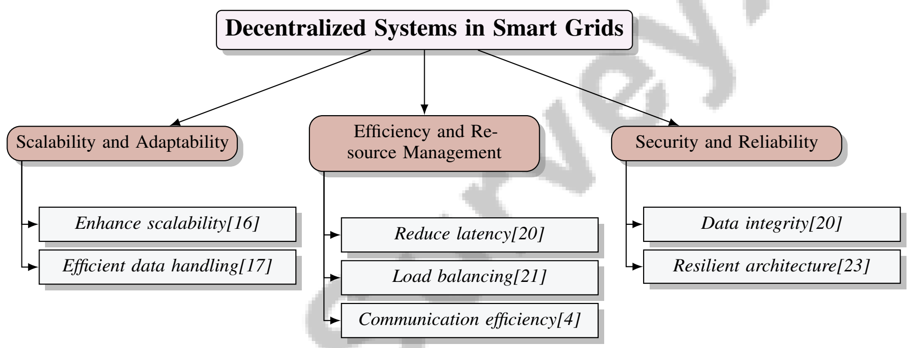

Figure 3: This figure illustrates the key roles of decentralized systems in smart grids, focusing on enhancing scalability and adaptability, improving efficiency and resource management, and ensuring security and reliability.

3.2 Role of Edge and Fog Computing

Edge and fog computing significantly enhance the efficiency and scalability of smart grids by decentralizing data processing and positioning computational tasks closer to data sources. This decentralization minimizes latency and improves response times, essential for meeting the real-time processing requirements of smart grids [24]. The integration of edge computing with IoT systems enables faster data processing and improved operational efficiency, facilitating more responsive and adaptive grid management [25].

Edge computing acts as an intermediary layer that integrates advanced technologies to bolster analytics capabilities for IoT data [26]. By deploying distributed edge analytics across multiple nodes in the edge-fog-cloud continuum, efficiency and performance are enhanced, leading to more effective resource utilization and decision-making [27]. The Smart-Edge-CoCaCo method exemplifies this integration by merging AI with edge computing to optimize computation, caching, and communication, enhancing distributed systems' efficiency and scalability [28].

Fog computing extends cloud services to the network edge, providing localized computing power and storage through mobile and stationary devices. This configuration allows for more efficient resource utilization and improved Quality of Service (QoS), crucial for addressing the dynamic demands of smart grid environments [29]. The incorporation of blockchain technology within decentralized architectures fosters a self-balancing system for dynamic monitoring and management of network resources [23].

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Adaptive algorithms empower nodes to make real-time decisions based on current data and resource availability, enhancing overall service delivery efficiency and robustness [30]. The DI-DCNC method optimizes routing paths and processing locations for live data streams, underscoring edge computing's role in improving efficiency and scalability [31]. Additionally, a pilot-based middleware facilitates better resource allocation decision-making through dedicated abstractions representing application tasks and execution strategies [32].

The scalability and robustness of decentralized environments are supported by frameworks that operate independently of a central authority, allowing seamless integration and management of distributed resources [33]. Lightweight frameworks for federated learning provide containerized solutions that support asynchronous learning, enhancing time efficiency and adaptability in edge and fog computing scenarios [26]. Moreover, a coded computing scheme achieves a Pareto-optimal tradeoff among storage, computation, and communication loads, optimizing resource allocation in smart grid environments [34].

To address communication constraints and maintain convergence in distributed optimization, refined quantization design methods are employed to ensure efficient data transmission and processing [27]. The Computation Offloading and Pricing Mechanism (COPM) optimizes access point allocation and edge service placement, enhancing smart grid efficiency and scalability [29]. Additionally, the Optimal Task Allocation Scheme (OTAS) utilizes Stochastic Integer Programming to determine the optimal number of tasks for local computation or offloading to edge servers, minimizing overall energy costs [35].

Advancements in distributed computing infrastructures and the development of transactive energy systems (TES) are enhancing the resilience, efficiency, and scalability of smart grid systems. These innovations address challenges posed by the increasing integration of distributed energy resources and the complexities of managing active distribution systems. By leveraging decentralized market solutions and robust financial frameworks, these systems are better equipped to meet modern energy management demands while ensuring operational privacy and security. Ongoing research into security simulation testbeds and the interplay between infrastructure and application usage further supports the evolution of these sophisticated energy solutions [13, 1].

4 Network Security in Smart Grids

4.1 Threats and Vulnerabilities in Communication

Smart grid communications face significant security challenges due to their distributed nature and the proliferation of connected devices. Cyber-attacks targeting decentralized optimization algorithms, such as those using the Alternating Direction Method of Multipliers (ADMM), pose substantial risks, necessitating robust detection and mitigation strategies [36]. Breaches in distributed controllers within cyber-physical systems (CPS) can lead to severe privacy violations and system disruptions [37].

Network congestion and increased latency due to high communication loads represent additional vulnerabilities, requiring effective transmission techniques to maintain data flow [38]. The Congestion-minimization with Bounded In-network Computing (C-BIC) problem highlights the need for optimal switch placement to manage traffic efficiently [39].

While blockchain technology offers security benefits, it also presents challenges like high energy consumption and scalability issues in fog environments, necessitating effective consensus mechanisms [12]. Fog computing's integration, although beneficial for reducing latency, introduces new security and privacy concerns [25]. The complexity of dynamic distributed systems requires innovative security techniques beyond traditional models [40]. Platforms like TESST enhance understanding of vulnerabilities in transactive energy systems, aiding in developing robust security measures [13].

As illustrated in Figure 4, the hierarchical categorization of threats and innovations in smart grid communication highlights the multifaceted nature of cybersecurity challenges, network vulnerabilities, and emerging security innovations. Addressing these threats requires advanced security protocols, efficient resource management, and innovative computing paradigms. Leveraging distributed software platforms and mobile edge cloud technologies can significantly enhance smart grid communication resilience, ensuring stable operation amidst decentralized power systems and distributed energy resources integration. These technologies support robust data processing and security, meeting real-time operational demands and maintaining reliability and efficiency in energy systems [13, 2, 1, 41].

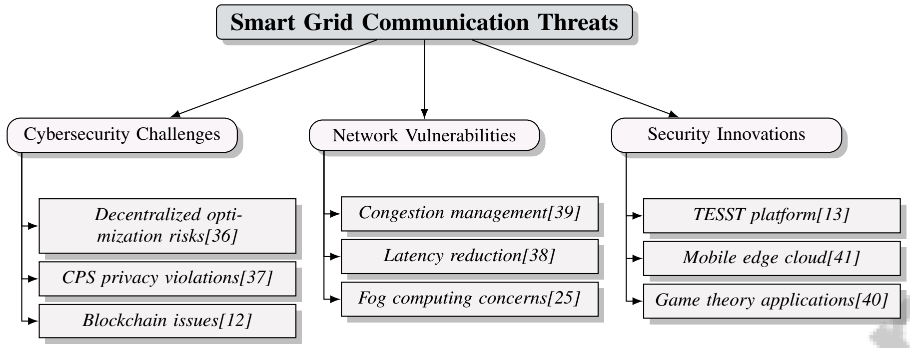

Figure 4: This figure illustrates the hierarchical categorization of threats and innovations in smart grid communication, highlighting cybersecurity challenges, network vulnerabilities, and security innovations.

4.2 Adaptive Security Algorithms

Adaptive security algorithms are vital for enhancing smart grid network security, offering dynamic responses to evolving cybersecurity threats. These algorithms maintain the integrity, confidentiality, and availability of communications. A notable advancement is the development of attack detection algorithms for ADMM, which identify and mitigate compromised nodes' impacts, ensuring robust decentralized optimization [36].

Game-theoretic approaches provide structured methods for analyzing security challenges in distributed systems, categorizing research into analytical, systems, and integration challenges to develop resilient security measures [40]. The brain-like based distributed control security (BLCS) architecture enhances security through cross-domain control among decentralized controllers [37].

Blockchain technology underpins adaptive security algorithms in smart grids, leveraging immutability and cryptographic principles to enhance security in fog computing. This framework addresses scalability, resource management, and security in distributed environments. Adaptive resource allocation strategies optimize resource distribution based on network conditions, enhancing security [39].

Trust management integrates data mining techniques to mitigate distributed systems' vulnerabilities, providing robust defenses against potential breaches and ensuring communication reliability [42]. Future research should improve interoperability, enhance user experience, and address cloud computing's scalability and security challenges [14].

Incorporating adaptive security algorithms is crucial for ensuring smart grid systems' resilience and operational integrity, particularly given the complexity and decentralization of transactive energy systems, which require robust protection against cyber threats and real-time data stream anomalies [13, 43, 8, 33, 11]. Employing dynamic security measures enables smart grids to withstand diverse cyber threats, ensuring stable energy management.

4.3 Decentralized Management and Access Control

Decentralized management and access control are essential for securing smart grid communications, offering robust solutions to distributed environments' challenges. These systems enhance data protection, regulatory compliance, and trust in data management, crucial for maintaining smart grid operations' integrity and reliability [44].

Integrating lightweight learning strategies, such as Representation Learning (ReL), into Zero Trust (ZT) architectures enhances security and decision-making processes, enabling adaptive security measures to dynamically respond to emerging threats [45].

A distributed hierarchy framework enhances smart grid resilience by enabling secure execution of critical functions through random coordinating agent selection, reducing targeted attack risks and ensuring continuous operation [43]. This method improves security, adaptability, and robustness in dynamic environments.

Blockchain technology plays a crucial role in decentralized management and access control, offering enhanced security, improved data integrity, and decentralized authentication mechanisms. These features foster trust in fog computing environments, ensuring secure and verifiable transactions and communications [46]. Blockchain's immutable records strengthen security by preventing unauthorized access and ensuring transparency and accountability.

Implementing decentralized management and access control in smart grids addresses distributed systems' complexities and security challenges, enabling fault-tolerant data management, enhanced resource access control, and mitigation of single points of failure through randomized control center selection. This approach improves resilience against cyber-attacks and ensures reliable operation in collaborative environments [23, 47, 43]. By adopting these strategies, smart grids achieve higher security and resilience, ensuring efficient energy resource management in interconnected environments.

5 Precise Measurements and Real-Time Data Processing

5.1 Real-Time Data Processing

Real-time data processing plays a critical role in enhancing decision-making and operational efficiency in smart grids by enabling immediate analysis and response to incoming data. This capability is indispensable for maintaining system stability and reliability, allowing for timely energy resource management. Advanced algorithms and innovative computing architectures, such as those used in Cloud, Edge, and Fog computing, are essential for optimizing performance and scalability in distributed systems [32, 48, 1, 49].

The IoTEnsemble method exemplifies the effectiveness of real-time analysis in detecting anomalies swiftly, thereby bolstering system reliability [50]. By utilizing IoT devices for continuous monitoring and data stream analysis, this method supports proactive energy management. Similarly, the Lambda-based anomaly detection method combines real-time processing with statistical models to enhance decision-making and operational efficiency in energy consumption monitoring [8].

Integrating IoT-aware Software-Defined Networking (SDN) with cloud architectures optimizes analytics task distribution, reducing network bandwidth usage and increasing service efficiency [51]. This architecture facilitates processing large data volumes, allowing smart grid systems to adapt dynamically to changing conditions. Experiments with AWS Lambda and PyWren demonstrate the practicality of distributed computing for real-time data processing in applications such as image processing and bulk synchronous tasks [52].

Edge computing significantly enhances real-time data processing by reducing latency and improving resource allocation [24]. By decentralizing data processing and bringing computation closer to data sources, edge computing improves the responsiveness of smart grid systems, facilitating efficient energy resource management. Additionally, grid-based data mining techniques enable real-time decision-making by efficiently retrieving frequent sequences for multiple users [42].

The DADP algorithm is an example of a real-time adaptive approach that adjusts processing strategies based on incoming data stream characteristics to optimize performance [53]. This adaptability is crucial for addressing the dynamic and heterogeneous nature of smart grid data, ensuring effective responses to varying conditions. Furthermore, a proposed distributed optimization method using reduced macro-iterations enhances operational efficiency in power distribution systems, demonstrating real-time data processing's potential to streamline grid operations [54].

As illustrated in Figure 5, the hierarchical structure of real-time data processing in smart grids highlights three primary categories: Advanced Algorithms, Anomaly Detection, and Distributed Architectures. Each category is supported by specific methods and technologies, showcasing their roles in enhancing operational efficiency and decision-making capabilities in smart grid systems.

Advancements in real-time data processing technologies are integral to smart grids' evolution, equipping them with tools for efficient, reliable, and responsive energy management. By integrating technologies such as transactive energy systems, Benders decomposition for capacity expansion modeling, and mobile edge cloud computing, smart grids can significantly enhance operational efficiency and decision-making capabilities. This integration addresses the complexities introduced by distributed energy resources and varying operational scenarios, supporting decentralized markets and robust financial frameworks, thereby contributing to modern energy systems' sustainability and resilience [13, 2, 41].

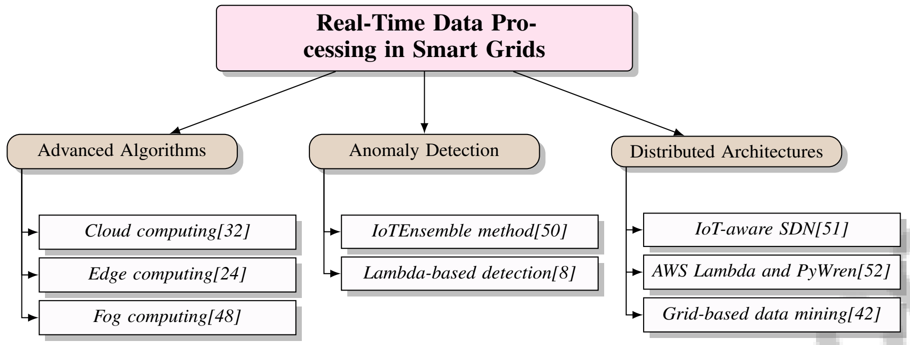

Figure 5: This figure illustrates the hierarchical structure of real-time data processing in smart grids, highlighting three primary categories: Advanced Algorithms, Anomaly Detection, and Distributed Architectures. Each category is supported by specific methods and technologies, showcasing their roles in enhancing operational efficiency and decision-making capabilities in smart grid systems.

5.2 Data Integrity and Provenance

Ensuring data integrity and provenance is crucial for reliable and accurate data processing within smart grids. The dynamic and distributed nature of these systems necessitates robust mechanisms to maintain data unaltered and accurately traced from origin to destination. Trust and reliability in energy management systems depend on data quality and authenticity, particularly in light of vulnerabilities to manipulation, leaks, and unauthorized access. Implementing frameworks like Honest Computing is vital, emphasizing transparency, integrity, and ethical practices in data management to ensure decisions in energy systems rely on trustworthy data lineage [13, 44, 11].

The DADP algorithm's adaptability demonstrates its ability to maintain performance in dynamic data environments where traditional methods may falter [53]. This adaptability is essential for preserving data integrity, allowing systems to adjust to varying data conditions and ensuring accurate processing. The ability to dynamically modify processing strategies based on real-time data characteristics is crucial for maintaining information fidelity throughout the data lifecycle.

Secure Multi-party Computation (SMC) enhances data integrity by dynamically allocating aggregation switches, minimizing congestion, and ensuring efficient data flow across the network [39]. By adjusting resource allocation based on current network conditions, SMC safeguards data integrity and provenance, preventing bottlenecks that could compromise data quality.

In smart grids, data provenance is vital for verifying data authenticity and origin, ensuring decisions are based on accurate information. Integrating provenance tracking mechanisms with distributed computing frameworks allows comprehensive monitoring and validation of data, enhancing energy management systems' reliability. Maintaining a transparent record of data origins and transformations significantly reduces risks of tampering and unauthorized access, thereby bolstering the integrity and security of energy consumption data. This approach aligns with Honest Computing principles, leveraging advanced technologies like distributed computing and cryptography to ensure reliable and auditable data handling throughout smart grid operations [55, 1, 13, 44, 8].

Emphasizing data integrity and provenance within smart grids highlights the need for advanced algorithms and computing architectures that adapt to changing conditions. These technologies form the backbone for reliable and accurate data processing, critical for the stability, efficiency, and security of modern energy systems. By leveraging Honest Computing principles, these technologies mitigate risks associated with data vulnerabilities, including unauthorized access and manipulation. Furthermore, integrating distributed computing infrastructures enables tailored applications that enhance data handling capabilities, fostering robust frameworks for data protection and regulatory compliance across various sectors, including energy [44, 1].

6 Energy Management Systems and Grid Optimization

6.1 Optimization Methods and Algorithms

Optimizing energy management systems within smart grids is crucial for enhancing operational efficiency and minimizing energy consumption. Advanced methods and algorithms, such as Dynamic Voltage Frequency Scaling (DVFS) and AI-driven resource management, address the complex challenges in high-performance computing (HPC) and distributed systems. These techniques facilitate optimized resource allocation and improved system performance, with energy-aware algorithms integrated across various HPC layers focusing on direct energy savings and performance gains. Data-driven solutions further enhance resource management in large-scale heterogeneous environments, catering to IoT applications and ensuring reliable service delivery, with experimental evaluations providing insights into their effectiveness [48, 3, 5].

Major cloud providers like Google Cloud and Microsoft Azure employ AI-centric solutions to optimize data center resource management, achieving significant energy savings [48]. Machine learning algorithms predict energy consumption patterns and optimize resource allocation, enhancing smart grid operational efficiency. AI integration allows for precise control over energy distribution, ensuring optimal and sustainable resource utilization.

The Nemesyst framework exemplifies deep learning application in optimizing refrigeration system control, managing energy consumption in response to grid demands [56]. By leveraging deep learning, Nemesyst enhances operational efficiency and reduces energy waste, highlighting the potential of AI-driven optimization methods in smart grids. Adaptive control strategies dynamically respond to changing grid conditions, ensuring effective energy management.

The MVFS-DVFS method formulates energy consumption as an optimization problem, showing optimal usage through adjacent frequencies from a discrete set [57]. This framework optimizes energy consumption at the task level, enabling efficient computing resource use and reducing overall energy costs. Optimizing frequency selection allows smart grids to achieve substantial energy savings while maintaining high performance.

The regularized Benders decomposition method significantly improves computational performance, solving large-scale capacity expansion models efficiently while maintaining resolution and accuracy [2]. This method effectively addresses large-scale optimization problems, providing scalable solutions for enhancing energy management efficiency in smart grids.

The distributed dynamic economic dispatch method achieves consensus on power generation and demand among agents without sharing sensitive information, maintaining privacy while ensuring efficient energy dispatch [4]. This approach underscores the importance of decentralized optimization methods for efficient energy distribution while preserving data privacy and security.

Integrating multi-scale stochastic simulation processes, as demonstrated in a five-step method for evaluating system adequacy and reliability, provides a comprehensive framework for optimizing energy management systems [58]. By incorporating planning and operational phases, this method enhances the reliability and robustness of smart grid operations, ensuring effective and sustainable energy resource management.

As illustrated in Figure 6, the hierarchical classification of optimization methods and algorithms in smart grids highlights AI-driven solutions, energy efficiency methods, and integration techniques. Collectively, these optimization methods and algorithms advance energy management systems in smart grids, equipping them with tools for efficient, reliable, and sustainable energy distribution. By integrating technologies such as transactive energy systems, mobile edge cloud computing, and enhanced anomaly detection methods, smart grids can significantly improve operational efficiency and resilience, effectively managing distributed energy resources, optimizing real-time data processing, and addressing security concerns [13, 2, 8, 41].

6.2 Distributed Computing Frameworks for Energy Management

Distributed computing frameworks are pivotal in enhancing energy management systems within smart grids by optimizing resource allocation and improving system performance. Utilizing advanced computational techniques such as tailored Benders decomposition and data-driven AI solutions, these frameworks effectively manage energy resources in modern smart grids. They address intricate and

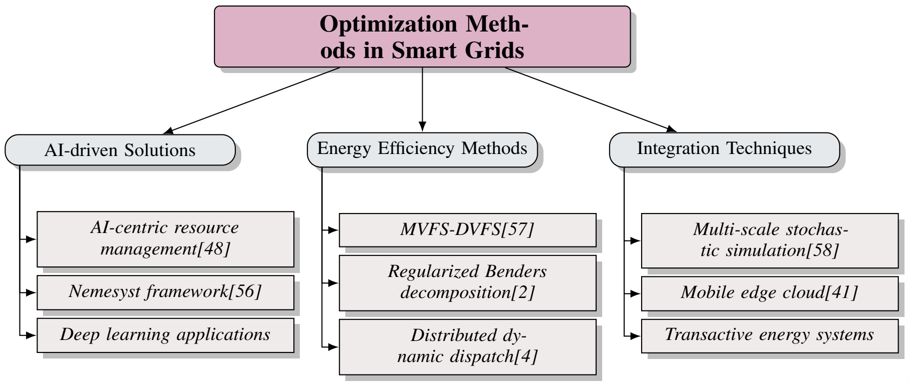

Figure 6: This figure illustrates the hierarchical classification of optimization methods and algorithms in smart grids, highlighting AI-driven solutions, energy efficiency methods, and integration techniques.

fluctuating demands, enabling high-resolution capacity expansion models and improving resource management in distributed computing environments, thus enhancing operational efficiency and reliability in response to real-time data and dynamic conditions [48, 2].

The Hierarchical Approximate-Factor Approach (HAF) exemplifies a distributed statistical method employing a hierarchical structure to analyze high-dimensional time series data, partitioning it across multiple computing units [18]. This method is essential for managing the vast data generated by smart grids, facilitating accurate and timely decision-making processes.

The Grid Architecture for Computational Economy (GRACE) introduces an economic-based distributed resource management framework that regulates supply and demand for resources, incentivizing participation from resource owners [15]. This robust mechanism optimizes resource allocation in smart grids, ensuring efficient and sustainable energy resource utilization.

The CDC method enhances distributed computing frameworks by allowing distributed deep neural network (DNN) models to tolerate failures while maintaining near-zero recovery latency [17]. This capability is vital for ensuring the reliability and robustness of energy management systems, particularly in environments characterized by high variability and uncertainty.

A proposed layered architecture, including a novel operating system, middleware, and component-structured applications, facilitates the development and management of distributed real-time embedded systems [21]. This architecture supports seamless integration of distributed computing frameworks with energy management systems, enhancing the adaptability and resilience of smart grids.

The ADMM method effectively solves optimization problems by enabling agents to negotiate their plans iteratively while ensuring local variable consistency across agents, facilitating faster convergence [22]. This method is particularly effective for optimizing energy distribution in smart grids, promoting efficient and equitable resource management.

The UCNC framework optimally manages packet routing and processing in distributed computing environments with mixed-cast traffic [20]. This framework enhances data communication and processing efficiency within smart grids, ensuring that energy management systems can respond effectively to changing conditions and demands.

These distributed computing frameworks significantly contribute to the advancement of energy management systems, providing essential tools for efficient, reliable, and sustainable energy distribution. By incorporating innovative strategies such as transactive energy systems (TES) and mobile edge cloud computing, smart grids can enhance operational efficiency and resilience. These approaches effectively manage energy resources in increasingly interconnected environments, addressing challenges posed by decentralized power system control while ensuring reliability, security, and optimized resource allocation through local data processing and real-time decision-making capabilities [13, 41].

7 Case Studies and Applications

7.1 Applications and Case Studies

The deployment of distributed computing frameworks in smart grids is exemplified by various case studies, demonstrating their effectiveness in optimizing resource management and enhancing operational efficiency. A notable instance is a distributed multi-agent system tailored for large-scale experiments, which reduced processing time and improved grid resource management for machine learning applications [59]. This system leverages distributed computing to efficiently allocate resources, showcasing its capability in managing complex computational tasks within smart grids.

Another critical case study involves integrating distributed computing with IoT systems for real-time energy consumption monitoring and control. Advanced algorithms and computing architectures process substantial data volumes, enabling smart grid systems to dynamically adapt to changing conditions and demands. This is crucial in environments with extensive IoT data streams, such as those from smart meters. AI-driven resource management techniques facilitate anomaly detection and adaptive resource management, ensuring reliable service delivery, as seen in real-time applications like GPU frequency scaling in cloud platforms [48, 1, 8]. This highlights distributed computing's role in enhancing smart grid operations' responsiveness and adaptability.

The implementation of blockchain technology within smart grids has significantly improved data security and integrity. By establishing a decentralized framework with consensus mechanisms and cryptographic techniques, blockchain enhances the reliability and security of smart grid systems. This technology ensures secure, verifiable, transparent, and tamper-proof transactions, mitigating risks associated with centralized servers and fostering trust among stakeholders in energy resource management [23, 46, 12]. This illustrates blockchain's potential in addressing security challenges in distributed environments, contributing to smart grid operations' robustness.

These case studies collectively demonstrate how distributed computing frameworks, including Computing Power Networks and middleware architectures for large-scale distributed systems, have transformed smart grid operations by enhancing resource allocation, flexible computing power scheduling, and fostering innovative application development tailored to these infrastructures [6, 26, 1, 60]. By leveraging advanced computational techniques, these frameworks promote efficient, reliable, and sustainable energy management, bolstering modern energy systems' stability and resilience.

7.2 Smart Grids in Urban Surveillance and Intelligent Systems

Smart grids are crucial to urban surveillance and intelligent systems, providing a robust infrastructure for efficient energy management and real-time data processing. The integration of distributed computing frameworks with smart grid technologies enhances urban monitoring and control capabilities by enabling efficient data collection and real-time analysis from diverse sources like smart meters. This synergy supports advanced anomaly detection and resource management, utilizing scalable processing power to improve decision-making in energy consumption patterns and overall grid management [1, 61, 26, 8, 6].

A primary application is deploying advanced sensor networks for continuous monitoring of environmental conditions, traffic patterns, and public safety. Integrated with smart grid systems, these sensors provide real-time data for advanced analytics, optimizing energy consumption and enhancing urban service efficiency. Techniques like supervised learning and statistical anomaly detection identify unusual consumption patterns and respond promptly to unexpected energy usage events. Edge computing integration allows faster data processing and analysis, reducing latency and improving system performance, essential for urban energy management [50, 3, 8]. Edge and fog computing capabilities enhance surveillance operations' responsiveness by processing data closer to the source.

Smart grids also advance intelligent transportation systems (ITS) by leveraging real-time data analytics to enhance traffic management, optimize flow, and reduce congestion. Integrating IoT technologies and edge computing enables dynamic distribution of IoT analytics, crucial for efficient traffic control and congestion avoidance. This integration fosters a responsive transportation infrastructure, improving urban mobility and reducing travel times [50, 51, 8, 41]. The synergy between IoT devices and smart grid infrastructure allows for traffic data collection and analysis, enabling dynamic traffic

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management and improved public transportation services, highlighting smart grids' potential to enhance urban mobility and mitigate transportation systems' environmental impact.

Smart grids also facilitate intelligent building management systems (IBMS) that optimize energy consumption while enhancing occupant comfort and safety. By integrating cloud computing, machine learning, and edge computing, these systems analyze real-time data from sensors and smart meters to detect anomalies in energy usage, manage resources effectively, and respond to potential security threats. This holistic approach ensures sustainable building operations while providing a secure and comfortable environment for occupants [41, 13, 50, 8, 11]. Distributed computing frameworks enable real-time monitoring and control of energy consumption, lighting, and HVAC systems, enhancing energy efficiency and contributing to urban infrastructures' sustainability and resilience.

Blockchain technology within smart grids strengthens urban surveillance and intelligent systems' security and integrity. A decentralized framework utilizing consensus mechanisms enhances data and transaction security and verifiability within the network. This approach mitigates potential security challenges associated with centralized systems, such as single points of failure. Blockchain's integration with cryptographic techniques ensures tamper-proof data management and facilitates transparent operations across distributed environments. In Federated Learning applications, blockchain preserves data privacy by eliminating direct data exchange while supporting collaborative model training, making it a promising solution for privacy-sensitive domains like healthcare and the Internet of Things (IoT) [47, 12].

The integration of smart grids with urban surveillance and intelligent systems offers substantial benefits in efficiency, security, and sustainability. By utilizing advanced computational techniques and innovative methodologies, smart grids enhance urban resource management through real-time data analytics and anomaly detection, enabling cities to evolve into smarter, safer, and more resilient entities. This transformation is facilitated by mobile edge cloud systems, which process data locally to reduce latency and improve efficiency, alongside artificial intelligence for adaptive resource management in complex distributed computing environments. Collectively, these technologies support developing transactive energy systems that address decentralized power management challenges while enhancing urban infrastructures' overall reliability and security [41, 48, 13, 50, 8].

8 Future Directions and Challenges

8.1 Emerging Technologies and Trends

The advancement of smart grids is shaped by emerging technologies that enhance efficiency, scalability, and reliability. Key developments include integrating horizontal partitioning techniques within the Hierarchical Approximate-Factor Approach (HAF), which extends its applicability to various time series data, thereby improving smart grid data management [18]. The Unified Control and Network Communication (UCNC) framework offers future research opportunities, particularly in adapting to complex network topologies. Incorporating machine learning into UCNC could optimize network performance and resource allocation [20].

Coded Distributed Computing (CDC) is promising for enhancing heterogeneous systems by reducing communication loads and mitigating straggler effects, essential for smart grid adaptability and efficiency. By leveraging coding theoretic techniques, CDC optimizes computational tasks across nodes, improving fault tolerance, privacy, and security. Further research into coding schemes and estimation algorithms could enhance CDC's applicability [62, 63, 64, 65].

Game-theoretic models offer insights into robust security strategies for distributed systems, analyzing strategic interactions within smart grids [40]. The application of Spatio-Temporal (ST) communication compression strategies to distributed optimization problems is expected to enhance smart grid efficiency and scalability, with ongoing research into alternative methods [66].

AI-driven resource management in fog computing is crucial for smart grids, improving security and scalability. Integrating online collection and forecasting with resource allocation addresses challenges from varying request rates and priorities, optimizing resource scheduling and enhancing system efficiency [67, 1, 68].

Emerging technologies, including transactive energy systems, advanced anomaly detection, distributed computing frameworks, and mobile edge cloud infrastructures, are shaping smart grids' future. These innovations address energy management challenges, enhancing the reliability, efficiency, and resilience of energy distribution networks [7, 41, 13, 4, 8].

8.2 Scalability and Efficiency in Distributed Systems

Scalability and efficiency are vital for deploying distributed systems in smart grids, affecting energy resource management and reliability. The heterogeneous nature of smart grid resources requires adaptive strategies to maintain low latencies and manage dynamic workloads. Addressing these challenges involves advanced computational techniques and robust algorithms [49].

A significant challenge in scalability and efficiency is network connectivity complexities and regularization parameter selection, influencing convergence speed in distributed learning. Future research should refine algorithms for scalability, exploring adaptive redundancy strategies that adjust to network conditions and workload distributions, optimizing resource allocation and ensuring efficient performance [69].

AI-augmented edge and fog computing frameworks can improve scalability and efficiency in smart grids, facilitating efficient resource management and enabling systems to adapt to varying conditions. Refining utility functions and developing robust distributed strategies can enhance system scalability and adaptability [70].

Hybrid approaches, such as combining Graph Neural Networks (GNN) with allocation strategies, offer future research potential. These approaches can be tailored to complex network structures, providing efficient and scalable solutions for smart grids [71]. Simplifying distributed computing models can help identify suitable models for specific applications, enhancing operational efficiency [72].

Future work should expand experimental scales, optimize algorithms, and address IoT security challenges [50]. Scalability issues in traditional middleware solutions, such as administrative rights and flexible management, highlight critical challenges [73]. The Smart-Edge-CoCaCo method's limitations illustrate scalability challenges in complex computational scenarios, relevant to future distributed systems [28]. Evolving grid and cloud computing standards and the learning curve for new technologies present significant challenges to scalability and efficiency [14]. Increased feedback in distributed systems may burden communication channels, affecting processing times and highlighting ongoing scalability and efficiency challenges [16].

9 Conclusion

This survey delves into the pivotal role of distributed computing in the advancement of smart grids, emphasizing the integration of network security, accurate measurements, energy management systems, grid optimization, and real-time data processing. These components are fundamental in elevating the efficiency, reliability, and sustainability of contemporary energy infrastructures. Distributed computing paradigms, including cloud, edge, and fog computing, are critical in enhancing resource allocation and system performance to meet the intricate demands of smart grids. The survey highlights the importance of decentralized systems in managing the burgeoning data and computational requirements, thereby facilitating effective energy distribution and consumption.

Network security emerges as a paramount concern, with adaptive security algorithms and blockchain technology offering robust solutions to vulnerabilities in distributed frameworks. These technologies safeguard the integrity, confidentiality, and availability of smart grid communications, mitigating the risks of cyber threats. Precise measurements and real-time data processing are crucial for accurate energy resource monitoring and control, enabling timely and efficient decision-making.

Energy management systems and grid optimization leverage advanced computational techniques to enhance operational efficiency and reduce energy consumption. The progression of distributed computing paradigms, such as coded distributed computing, further augments the scalability and efficiency of smart grids, providing a robust computational foundation for effective energy management and system optimization.

The survey concludes that the integration of these technologies is essential for the development of resilient and sustainable smart grid systems capable of meeting the growing demands of modern energy management and distribution networks. By harnessing advancements in distributed computing, network security, and real-time data processing, smart grids can achieve superior operational efficiency and resilience, thereby contributing to the sustainability and stability of energy systems.

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