

Review article

Survey of energy-efficient fog computing: Techniques and recent advances

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ABSTRACT

Undoubtedly, energy efficiency forms a fundamental pillar of the fog computing model. Processing data at the network's edge leads to a substantial reduction in energy consumption when contrasted with the alternative of transmitting all data to remote data centers, typically associated with cloud computing. This energy-saving approach not only promotes a more environmentally friendly footprint but also serves to prolong the operational life of battery-powered IoT devices, a particularly critical aspect, especially in remote or challenging-to-access environments. Thus, fog computing plays a crucial role in the operation of massive energy-saving IoT or green IoT networks. This study offers a comprehensive survey of recent research endeavors focused on achieving energy-efficient fog computing and eco-friendly fog computing solutions for IoT networks. The article initiates with an introductory overview of fog computing and subsequently delves into an in-depth exploration of various energy-conservation techniques tailored for fog computing environments. These techniques encompass energy-conscious architectural designs, data aggregation and compression strategies, low-power hardware implementations, energy-aware scheduling methods, task offloading mechanisms, resource utilization optimization, virtualization techniques, and energy harvesting approaches. In addition, this investigation introduces novel methodologies and outlines prospective research pathways to bolster the energy efficiency of fog computing. Moreover, practical applications are presented to highlight the potential advantages and obstacles associated with deploying energy-conscious strategies, providing insights into their effectiveness and practical implications in real-world scenarios. Essentially, this article can be considered a roadmap towards the realization of a sustainable fog computing ecosystem for extensive IoT networks. In addition, opens the door for interested researchers to follow and continue the vision of energy-efficient computing.

1. Introduction

1.1. Background and motivation

The exponential growth of IoT devices is nothing short of astounding. Recent estimates indicate that the global number of IoT devices reached a staggering 50 billion in 2020, and this number is projected to grow to

over 75 billion by 2025 (Palaniswami et al., 2020). Each of IoT devices generates an influx of data that needs to be collected, processed, and analyzed, demanding efficient and scalable solutions to prevent network congestion and ensure real-time decision-making (Verma et al., 2017).

Traditional cloud computing, while effective, faces significant challenges in terms of latency, bandwidth consumption, and energy inefficiency when confronted with the sheer scale of IoT deployments.

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This is where fog computing steps in. Fog computing extends the cloud's capabilities to the edge of the network, enabling data processing closer to the source, thereby reducing latency and conserving valuable network resources (Hu et al., 2017). It is a paradigm well-suited to the IoT landscape, where low-latency communication is often mission-critical (Bittencourt et al., 2018).

Energy efficiency is a cornerstone of the fog computing model. By processing data at the edge, energy consumption is significantly reduced when compared to transmitting all data to distant data centers (cloud computing). The energy-efficient fog computing can lead to an impressive reduction in power consumption for IoT networks (Malik et al., 2021; Asghari and Sohrabi, 2024; Guo et al., 2024; Srirama, 2024; Hazra et al., 2023). This reduction not only contributes to a smaller carbon footprint but also extends the lifespan of battery-powered IoT devices, a vital consideration in remote or inaccessible environments (Lorincz et al., 2019; Shahidinejad et al., 2021a). Thus, fog computing plays a crucial role in the operation of massive IoT networks.

This article aims to explore the paradigm of energy-aware fog computing, focusing on strategies and technologies that optimize energy consumption while maximizing performance and environmental sustainability. The discussion encompasses various facets of energy awareness.

1.2. Literature and our contribution

Various research endeavors have extensively defined and elucidated fog computing, each contributing uniquely to different facets within the paradigm. Numerous review and survey papers have emerged to offer an insightful perspective on fog computing. Table 1 offers a comprehensive summary comparison of the main interesting articles in the literature based on the key points, contributions, and main focuses.

This paper endeavors to offer a holistic perspective on the landscape of energy-aware fog computing and the inherent challenges within this paradigm. Moreover, it delineates and recommends several prospective research avenues in energy-aware fog computing to solidify the vision of an energy-efficient fog computing landscape in the future. More specifically, the significant contributions and novel aspects introduced in this study encompass:

- ✓ This study provides an in-depth examination and critical evaluation of various energy-efficient methodologies in fog computing. In addition, the article consolidates a range of techniques such as clustering, distributed architectures, data aggregation, compression, task offloading, and AI-driven optimizations, elucidating their mechanisms, benefits, limitations, and application scenarios. This comprehensive analysis offers a holistic understanding of energy-saving strategies in fog computing.
- ✓ The study incorporates practical case studies and real-world applications to illustrate the efficacy and challenges of implementing energy-aware strategies in fog computing. These case studies cover diverse aspects like distributed architectures, task offloading, energy harvesting, and optimized communication protocols, providing insights into their effectiveness and potential challenges when applied in practical scenarios.
- ✓ The research outlines and proposes several promising future research directions in energy-aware fog computing. In addition, the article introduces suggestions for enhancing energy efficiency, such as AI-driven optimizations, hybrid energy harvesting techniques, edge intelligence, optimized communication protocols, and dynamic resource management. These propositions serve as significant stepping stones for researchers to explore and develop more efficient and sustainable fog computing solutions.
- ✓ This study offers novel insights and critical analyses. In addition, the article consolidates discussions on challenges and opportunities in energy-efficient fog computing, fostering a deeper understanding of the field and guiding researchers toward more effective and

sustainable solutions. The synthesis of these discussions and insights serves as a valuable resource for researchers, practitioners, and stakeholders in the domain of fog computing and energy efficiency.

1.3. Paper organization

The article is structured as follows: Section 2 covers various energy-aware techniques in fog computing, including architectural designs, data strategies, hardware implementations, scheduling, task offloading, resource optimization, virtualization, and energy harvesting. Section 3 explores future research opportunities, proposing ideas for further exploration. Lastly, Section 4 summarizes the study's conclusions.

2. Energy-aware techniques for fog computing

This section extensively explores various methodologies to optimize energy usage in fog computing. It covers energy-efficient architectural designs, data aggregation, compression, task offloading, low-power hardware, energy-conscious scheduling, resource utilization, virtualization advancements, and energy harvesting methods, as shown in Fig. 1. It aims to provide a comprehensive perspective on energy-aware strategies within fog computing. Additionally, Table 9 summarizes all the discussed energy-aware techniques in this section.

2.1. Energy-aware fog computing architecture

Energy-aware fog computing architecture is a framework designed to minimize energy consumption while delivering low-latency, high-performance computing at the network edge. This architecture aims to strike a balance between computing tasks offloaded to fog nodes and those processed in the cloud. It leverages energy-efficient hardware, intelligent workload distribution, and optimization algorithms to ensure that computational resources are used efficiently, reducing the environmental footprint of the fog computing infrastructure (Bellavista et al., 2019). Energy-aware fog computing architectures primarily fall into two categories: clustered architecture and distributed architecture, with each tailored to specific applications and deployment scenarios (Mahmud et al., 2018). Notably, clustered architecture has gained prominence as the preferred approach for optimizing energy-efficient communications (Cao et al., 2017; Hong and Varghese, 2019).

2.1.1. Clustered fog computing architecture

Clustered architecture within the realm of fog computing is a strategic approach devised to heighten energy efficiency and performance by arranging fog nodes into organized clusters. This architectural model categorizes sensor nodes into clusters of varying sizes, contingent upon considerations such as their geographical location, density, and proximity to the base station or fog node. Within each of these clusters, a proficient sensor node is designated as the cluster head, endowed with the responsibility of overseeing communication within the cluster. Member sensor nodes within the cluster are tasked with gathering and dispatching their data to the cluster head, which, in turn, amalgamates the data and channels it forward to the designated fog node. For the purpose of optimizing the system's overall efficiency, relay fog nodes are selected based on criteria including their residual energy and current workload (Hu et al., 2017; Sabireen and Neelanarayanan, 2021). The core operational methodologies underpinning clustered architecture in fog computing encompass the following (Hong and Varghese, 2019; Shirazi et al., 2017): (i) Node Clustering: Fog nodes are assembled into clusters, with the criteria for clustering being rooted in geographical proximity, specific application requirements, or dedicated functions. (ii) Task Offloading: Clusters make informed decisions regarding the location for data processing, with options encompassing local processing within the cluster or transmitting data to the cloud, all contingent on factors like latency constraints and resource availability. (iii) Resource Sharing: Within the boundaries of a cluster, resources such as

Table 1
Summary comparison of the main interesting articles in the literature.

Ref.	Key Points and Contributions	Architecture	Aggregation and compression	Low power hardware	Scheduling	Task offloading	Switching on/off	Virtualization	Energy Harvesting
(Malik et al., 2021)	Defined fog computing within 6G-enabled IoT, emphasizing energy-efficient solutions like task offloading, dynamic switching on/off, and energy harvesting to reduce energy use and support large-scale IoT deployments.	✓				✓	✓		✓
(Kaur and Kaur, 2021)	Discussed how energy-efficient routing and scheduling techniques improve the fog computing paradigm by optimizing data processing and resource allocation.				✓				
(Bozorgchenani et al., 2020)	Discussed a comprehensive framework for computation offloading with energy harvesting optimizes task transfer and resource utilization between devices and fog nodes.					✓			✓
(Sadri et al., 2022)	Discussed challenges in fog computing data reduction, focusing on balancing energy efficiency, data integrity, and accuracy in dynamic IoT environments.		✓						
(Zhang et al., 2018)	Categorized VM migration techniques—live, pre-copy, and post-copy—and discussed the challenges like downtime, data integrity, and resource allocation, which are crucial for improving energy efficiency in fog computing.							✓	
(Hu et al., 2017)	Reviewed the fog computing architecture, emphasizing key technologies virtualization and resource managementthat support energy-efficient integration.			✓				✓	
(Rault et al., 2014)	Evaluated various strategies, aggregation and compression, low-power hardware, and dynamic switching for enhancing energy efficiency in fog computing.		✓	✓			✓		✓
This article	Explores energy-efficient methodologies in fog computing, reviewing various techniques and practical case studies on implementation challenges. In addition, suggests future directions, including AI-driven enhancements and dynamic resource management.	✓	✓	✓	✓	✓	✓	✓	✓

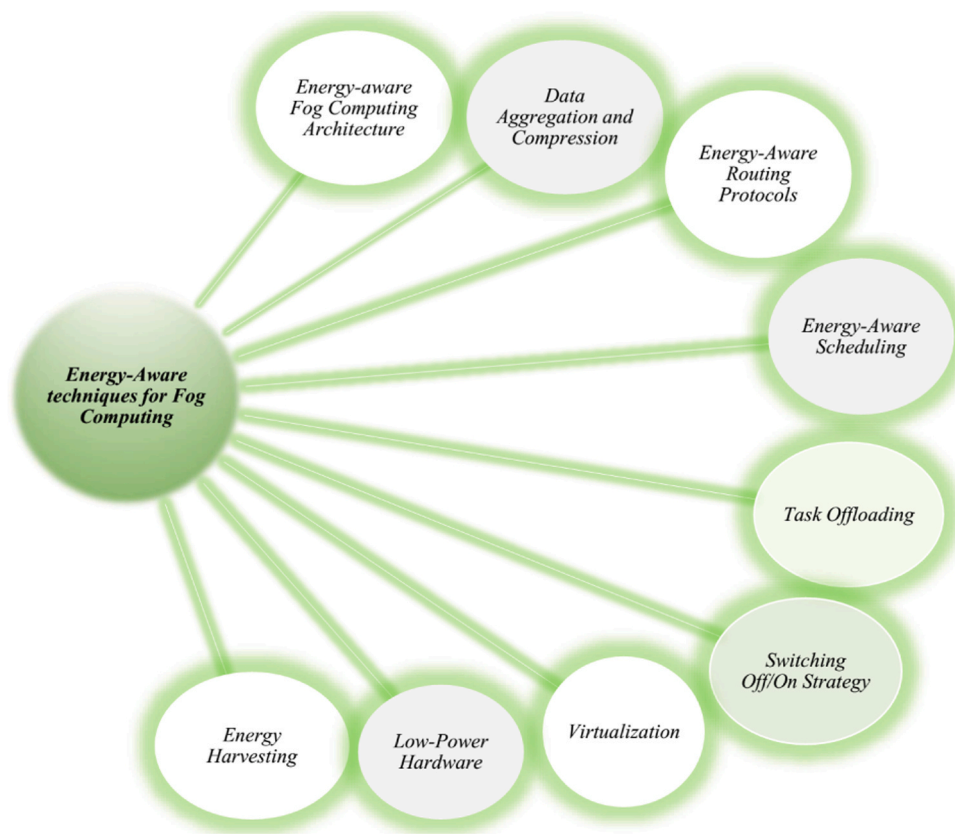


Fig. 1. Energy-aware techniques for fog computing.

computational power and storage are collectively utilized, mitigating the necessity for individual nodes to shoulder intricate computations. Since the clustered architecture is highly adept in fulfilling the requisites of applications demanding swift data processing, real-time analytics, and energy-conserving data exchange. Thus, the recommended applications for clustered architecture span a broad spectrum and include, but are not confined to, domains such as smart cities, Industrial IoT, healthcare, and autonomous Vehicles (Zhang and Li, 2017). It is worth noting that the clustered architecture brings forth several additional benefits, including enhanced scalability, prolonged network longevity, diminished routing delays, reduced network congestion, and more effective management of channel access (Sabireen and Neelanarayanan, 2021).

In clustered architecture, the key challenge is selecting efficient cluster heads to enhance energy efficiency. Various strategies have been proposed to address this issue. Sun et al (Sun et al., 2019). suggested establishing a communication hierarchy among cluster heads based on their proximity to the central fog node, with certain cluster heads acting as relays to facilitate data transmission. Khalifeh et al (Abid and Darabkh, 2020). advocate for grouping sensor nodes into clusters and selecting cluster heads based on remaining energy. Rafi et al (Rafi et al., 2019). propose distributing sensors into clusters and selecting the cluster head based on workload. Wang et al (Wang et al., 2019). distribute sensor nodes into clusters and designate cluster heads using fog nodes, considering factors like remaining energy and communication reliability. Omoniwa et al (Omoniwa et al., 2018). proposed a mobile relay fog node positioned between sensor nodes and central fog nodes or cloud servers, chosen for its energy-efficient transmission capabilities. Bozorgchenani et al (Bozorgchenani et al., 2018). introduced a clustered approach for task offloading among fog nodes, optimizing energy and time by categorizing fog nodes based on power sources and dynamically allocating tasks.

Case study of leveraging clustered fog computing architecture for

enhancing energy efficiency, real-time traffic management in a smart city (Ning et al., 2019; Baccarelli et al., 2017). A smart city project aimed to reduce traffic congestion, improve public transportation, and enhance safety through real-time traffic management. A clustered fog computing architecture was adopted to enable efficient data processing and decision-making. In this case, fog nodes were strategically clustered at key intersections and traffic hubs within the city. Each cluster head was responsible for collecting and processing traffic data from sensors, surveillance cameras, and vehicle-to-infrastructure communication. These cluster heads coordinated with a central traffic management system hosted in the cloud to provide real-time traffic updates and control signals. The clustered fog computing architecture significantly improved the efficiency of traffic management in the city. With reduced data transmission to the cloud, the system achieved an average energy savings of 15 %. Low-latency decision-making allowed for dynamic traffic signal adjustments, resulting in a 20 % reduction in traffic congestion and a 10 % reduction in travel times.

2.1.2. Distributed fog computing architecture

Distributed architecture decentralizes the responsibilities typically carried out by central nodes or cluster heads in clustered architecture. Instead of concentrating data processing and resource management in clusters, this approach spreads the tasks across a broader set of fog nodes. Each fog node within the network can independently process data, execute applications, and manage resources (Lindsay et al., 2021; Dastjerdi et al., 2016). The core operational methodologies underpinning distributed architecture in fog computing encompass the following (Jin et al., 2018; Naha et al., 2018): (i) Decentralized Processing: Fog nodes are equipped to independently handle data processing and application execution, reducing the need for centralized cluster heads. (ii) Local Decision-Making: Fog nodes autonomously make decisions about data processing based on factors like latency requirements and resource availability, without relying on a central cluster head. (iii)

Resource Autonomy: Each fog node is self-reliant in terms of resource management, leading to distributed resource sharing and optimized energy utilization. Distributed architecture is suitable for a variety of applications, particularly those that require distributed data processing, improved resource sharing, and low-latency communication. Some recommended applications for distributed architecture or decentralized fog computing include but are not limited to (Abdali et al., 2021): (i) **Distributed Edge Analytics:** Applications where data analytics is performed in a distributed manner across the network, such as predictive maintenance in industrial settings. (ii) **Decentralized Edge AI:** Edge AI applications that involve distributed machine learning models for tasks like image recognition and natural language processing. (iii) **Edge-Based Content Delivery:** Applications where content, such as video streaming or content caching, is distributed and processed across multiple fog nodes for reduced latency.

The primary challenge confronting distributed fog computing architecture lies in the effective management and orchestration of the decentralized resources and services. Unlike clustered architectures, where the role of cluster heads is well-defined, distributed fog computing relies on individual fog nodes to independently process data, execute applications, and manage resources (Ni et al., 2017). This decentralization, while offering advantages in terms of resilience and scalability, introduces several key challenges, which are discussed in detail below:

- **Resource variability and heterogeneity:** In a distributed fog computing environment, fog nodes may vary significantly in terms of computational power, storage capacity, and available resources. This variability can make it challenging to allocate tasks and resources effectively. Some fog nodes may be better equipped to handle certain tasks, while others may struggle due to resource limitations (Hong and Varghese, 2019; Jamil et al., 2022).
- **Load balancing:** Ensuring that the computational load is evenly distributed across distributed fog nodes is a complex task. The lack of a central coordinator, as seen in cluster-based architectures, makes load balancing a challenging endeavor. Suboptimal load balancing can result in uneven resource utilization and performance issues (Kaur and Aron, 2021).
- **Resource discovery and provisioning:** Discovering available resources and services across distributed fog nodes and provisioning them for specific tasks is a non-trivial problem. Effective mechanisms are required to identify suitable fog nodes for specific applications and to dynamically allocate resources as needed (Etemadi et al., 2020).
- **Fault tolerance and resilience:** With the absence of centralized control, distributed fog computing architectures need to address fault tolerance and system resilience effectively. Failures in individual fog nodes or network segments should not lead to widespread service disruption. Ensuring data integrity and reliability in such a decentralized system is a critical challenge (Reyana et al., 2023).
- **Security and privacy:** The decentralized nature of distributed fog computing raises security and privacy concerns. Data transmitted and processed across a multitude of fog nodes may be more vulnerable to breaches, and privacy issues may arise as data moves through various nodes. Establishing secure communication and data protection mechanisms is paramount (Mann, 2022).

To address these challenges, ongoing research and development in distributed fog computing architecture focus on resource discovery mechanisms, adaptive load balancing algorithms, fault tolerance strategies, and security measures tailored to decentralized systems.

Case study of leveraging distributed fog computing architecture for enhancing energy efficiency, smart agriculture system (Qureshi et al., 2021; Alharbi and Aldossary, 2021). A smart agriculture system aims to optimize crop production, minimize resource usage, and reduce environmental impact. Distributed fog computing architecture was implemented in this case study to enhance energy efficiency and real-time

decision-making in the field. In this scenario, multiple IoT devices and sensors were deployed across a large agricultural field. Distributed fog computing architecture was used to process data at the edge, minimizing latency and conserving energy. Fog nodes, distributed throughout the field, independently processed sensor data and executed localized control algorithms. Data was also transmitted to a central cloud for historical analysis. The implementation of Distributed fog computing reduced the energy consumption of the agricultural system significantly. By processing data at the edge, the system achieved an average energy saving of 25 % compared to a traditional cloud-centric approach. This architecture enabled real-time decisions for irrigation, fertilization, and pest control, leading to improved crop yields and resource utilization.

Table 2 provides a side-by-side comparison of clustered and distributed fog computing architectures, highlighting their differences in terms of mechanisms, benefits, limitations, and application suitability.

Generally, in distributed fog computing, energy efficiency is achieved by decentralizing computational tasks, reducing redundant data transfers, and optimizing the use of local resources. This decentralized approach can result in notable energy savings, with some studies indicating reductions in energy consumption by up to 30 % when compared to traditional cloud-centric architectures (Alharbi and Aldossary, 2021; Das and Inuwa, 2023). Achieving these savings hinges on effective load balancing mechanisms and resource autonomy for individual fog nodes. In contrast, clustered fog computing centers on organizing fog nodes into clusters, which can result in energy-efficient localized data processing and shared resources. Studies suggest that clustered fog computing can lead to significant energy savings, with reductions in power consumption by up to 20 % (Malik et al., 2021). However, to maximize these savings, careful cluster management, dynamic load balancing, and efficient task offloading to the cloud are essential considerations. In both architectural approaches, the choice of suitable applications, effective resource management, and scalability are vital

Table 2
Comparison of clustered and distributed fog computing architectures.

Architecture Aspect	Clustered fog computing architecture	Distributed fog computing architecture
Mechanisms for enhancing energy efficiency	Processing data within clusters, redundant data transfers to the cloud are minimized, saving energy and reducing network congestion. In addition, nodes within a cluster can share resources efficiently, leading to better utilization of computing power and reduced power wastage.	Avoiding the concentration of data processing and resource management in specific cluster heads. This results in more equitable energy distribution and lower power consumption across the fog network. The decentralized nature of this architecture minimizes data transfers, leading to reduced network traffic and lower energy consumption.
Benefits	Efficient resource utilization within clusters. Improved fault tolerance with redundancy within clusters. Suitable for real-time applications in smart cities and IoT.	Enhanced resilience due to decentralization. Scalable and adaptable to network growth. Lower latency for edge applications.
Limitations	Management and coordination of cluster heads can be complex. Initial setup and configuration of clusters can be time-consuming. Limited resources within some clusters.	Load balancing and resource allocation complexities. Security and privacy challenges in decentralized environments.
Applications	Smart cities, Industrial IoT, healthcare, and autonomous Vehicles	Decentralized IoT, edge analytics, distributed sensor networks and edge-based AI applications.

factors for optimizing energy efficiency (Hu et al., 2017).

2.2. Data aggregation and compression strategies

Energy-efficient data management is a paramount concern, and energy-aware data aggregation and compression strategies have emerged as vital components. These strategies involve the aggregation of data at the network edge and the compression of data before transmission to minimize energy usage, enhance system performance, and prolong the operational lifespan of IoT edge devices (Chen et al., 2018).

2.2.1. Data aggregation

Data aggregation in fog computing offers an array of techniques for optimizing energy efficiency and network performance. Each technique is suited to different application scenarios, and selecting the right one depends on the specific requirements and trade-offs related to data reduction, processing, and insights (Sadri et al., 2022). To achieve the goal of saving energy and improving network efficiency, the following methodologies are employed:

- *Spatial data aggregation:* Devices in close proximity collect data and aggregate it before transmission. This approach reduces the number of data packets transmitted over long distances, conserving energy and minimizing network congestion (Idrees and Al-Qurabat, 2021).
- *Temporal data aggregation:* Data is aggregated over time, with devices collecting and storing data locally before transmitting it. This reduces the frequency of data transmission, saving energy and bandwidth (Ali et al., 2021).
- *Hierarchical data aggregation:* Data is aggregated in a hierarchical structure, with data collected and summarized at multiple levels within the fog network. Higher-level fog nodes receive aggregated data from lower-level nodes, reducing energy consumption as data moves up the hierarchy (Nalayini and Prakash, 2023).

Data aggregation in fog computing encompasses various techniques, each with its own advantages and limitations:

- Centroid-Based aggregation:* Data points are aggregated by calculating the centroid of a group of data points. This is useful for location-based data in applications like smart transportation, where the average location of vehicles can provide traffic information (Akbari et al., 2022).
- Statistical aggregation:* Data is aggregated using statistical methods like averaging, summing, or taking the maximum/minimum values. This approach is common in sensor networks for environmental monitoring and industrial IoT applications (Sun et al., 2012).
- Event-Driven aggregation:* Data is aggregated based on predefined events or triggers. This technique is valuable for applications where data aggregation is event-dependent, such as in healthcare for patient monitoring (Sun et al., 2019).
- Window-Based aggregation:* Data is aggregated within a fixed time window, and the results are transmitted at the end of the window. It's commonly used in real-time data stream processing for applications like anomaly detection (Bhatia, 2020).
- Cross-Domain aggregation:* In this technique, data from different domains are aggregated. For example, environmental data and location data may be combined to provide insights into air quality in a specific area (Alzoubi et al., 2021).

Table 3 provides a comprehensive summary comparison, encompassing data aggregation techniques, energy-saving methodologies, advantages, and limitations.

2.2.2. Data compression

Data compression plays a pivotal role in fog computing by

Table 3
Comparison of data aggregation techniques.

Technique	Methodology for Saving Energy	Advantages	Limitations
Centroid-Based	Spatial and Temporal	Location-based insights, reduced data traffic	Limited applicability, may not suit all data
Statistical	Spatial and Temporal	Efficient for sensor data, simplifies analytics	Loss of raw data details, may not capture trends
Event-Driven	Temporal	On-demand data aggregation, real-time updates	Limited to event-triggered applications
Window-Based	Temporal	Real-time data processing, controlled bandwidth	Requires careful window size selection
Cross-Domain	Spatial	Holistic insights, combines diverse data types	Complex data integration, potential for errors

significantly reducing data sizes, thereby saving energy during transmission and processing. The choice of compression technique depends on the specific application's data preservation requirements, data patterns, and trade-offs between data loss and compression ratios (Dash et al., 2019). Data compression achieves this through the following approaches (Jayasankar et al., 2021):

- *Reduced data volume:* By compressing data, the volume of information transmitted across the network is significantly reduced, leading to less energy consumption during data transmission.
- *Less data processing:* Smaller data packets are easier to process, and compression can take place at the edge, reducing the computational load on fog nodes and IoT edge devices, thus conserving energy.
- *Lower bandwidth usage:* Compressed data requires less bandwidth for transmission, leading to energy savings, especially in scenarios where limited bandwidth is available.

Data compression in fog computing employs various techniques, each with distinct advantages and limitations:

- Lossless compression:* Lossless compression algorithms reduce data size without losing any information. They are suitable for applications that require exact data preservation, such as medical data storage (Elakkiya and Thivya, 2021).
- Lossy compression:* Lossy compression sacrifices some data details to achieve higher compression ratios. It is beneficial in applications where minor data loss is acceptable, such as multimedia content delivery (Elakkiya and Thivya, 2021).
- Differential compression:* This technique involves sending only the differences between consecutive data points, which is useful for data that exhibits minimal changes over time, such as sensor readings (Giouroukis et al., 2020).
- Run-Length Encoding (RLE):* RLE identifies sequences of identical values and replaces them with a count, reducing the data size. It is efficient for specific data patterns (Díaz-Domínguez et al., 2022).
- Dictionary-Based compression:* Dictionary-based algorithms create a dictionary of frequently occurring data patterns and encode data based on this dictionary, reducing redundancy (Jain and Lakhtaria, 2016).

Table 4 offers a comprehensive comparative summary, covering data compression techniques, methodologies for energy conservation, as well as their respective advantages and limitations.

Case study of energy-aware data aggregation and compression, Industrial IoT (Liu et al., 2021). The manufacturing plant had a multitude of sensors and devices generating large volumes of data, including

Table 4
Comparison of data compression techniques.

Technique	Advantages	Limitations
Lossless	Exact data preservation, data integrity	Moderate compression ratios
Lossy	High compression ratios, acceptable data loss	Irreversible data loss, limited applications
Differential Compression	Suitable for data with small changes over time	Data dependencies, lossy for some data
Run-Length Encoding (RLE)	Simple and efficient for certain data patterns	Limited applicability, limited compression
Dictionary-Based	Adaptive to data patterns, high compression ratios	Dictionary management, resource-intensive

temperature, pressure, and machine performance metrics. Transmitting and processing all this data in real-time consumed excessive energy and led to latency issues, affecting the production process. A manufacturing facility sought to enhance its operational efficiency and reduce energy consumption. To achieve this, the facility implemented energy-aware data aggregation and compression strategies within its fog computing architecture. Adopted energy-aware data aggregation and compression strategies as summarized in Fig. 2. The fog nodes were responsible for data aggregation and initial compression, ensuring only essential data was transmitted to the cloud for long-term storage and in-depth analysis. Real-time decision-making was primarily carried out at the fog level, resulting in reduced latency and efficient energy utilization. The implementation of energy-aware data aggregation and compression strategies yielded significant benefits: (i) Energy savings: Energy consumption related to data transmission and processing was reduced by approximately 35 %. IoT edge devices and fog nodes exhibited prolonged operational lifespans. (ii) Latency reduction: Real-time decision-making was achieved with lower latency, improving the facility’s overall productivity and reducing the risk of production delays. (iii) Enhanced reliability: The streamlined data management system increased the reliability of sensor networks, resulting in more consistent and accurate data for process control.

In general, energy-aware data aggregation and compression strategies in fog computing have the potential to achieve significant energy savings. While the actual energy savings can vary depending on the specific deployment and the nature of data, studies have shown that these strategies can lead to reductions in energy consumption ranging from 10 % to 40 % (Swaminathan et al., 2021). The key consideration for achieving these energy savings lies in optimizing the balance between data reduction and the application’s requirements. Effective algorithms for data filtering, aggregation, and compression are crucial to ensuring that only essential data is transmitted while minimizing

energy-intensive data processing and transmission. Additionally, the choice of compression algorithms and their settings can significantly impact energy savings. Proper implementation, continuous monitoring, and fine-tuning of these strategies are essential for maximizing energy efficiency while maintaining data integrity and application performance.

2.3. Energy-aware routing protocols

Energy-aware routing protocols are vital for achieving energy-efficient data transmission and communication in fog computing. The choice of protocol depends on the specific application requirements, the available energy resources, and the trade-offs between latency and energy consumption (Haseeb et al., 2023). Energy-aware routing protocols focus on energy conservation by considering the following methodologies (Kaur and Kaur, 2021):

- *Path selection:* These protocols prioritize routes with lower energy consumption, often favoring paths through well-powered fog nodes or energy-efficient communication links. This reduces the energy required for data transmission.
- *Node selection:* Energy-efficient routing decisions involve selecting nodes with sufficient energy reserves to relay data. It ensures that energy-constrained nodes are not overburdened, prolonging their operational life.
- *Load balancing:* Effective load balancing spreads data transmission and processing tasks evenly across available resources, preventing resource exhaustion and minimizing energy wastage.

Energy-aware routing protocols encompass several techniques and approaches, each tailored to specific scenarios and applications:

- Proactive protocols:* These protocols establish routes in advance and maintain them, ensuring low-latency routing decisions. Examples include Optimized Link State Routing (OLSR) (Alghamdi et al., 2019) and Destination Sequenced Distance Vector (DSDV) (Vijarania et al., 2023).
- Reactive protocols:* Reactive protocols establish routes only when needed, conserving energy when data transmission is sporadic. Examples include Ad Hoc On-Demand Distance Vector (AODV) (Darabkh and Alkhader, 2022) and Dynamic Source Routing (DSR) (Yura et al., 2020).
- Multipath routing:* Multipath routing creates multiple paths for data transmission, distributing traffic and reducing the burden on

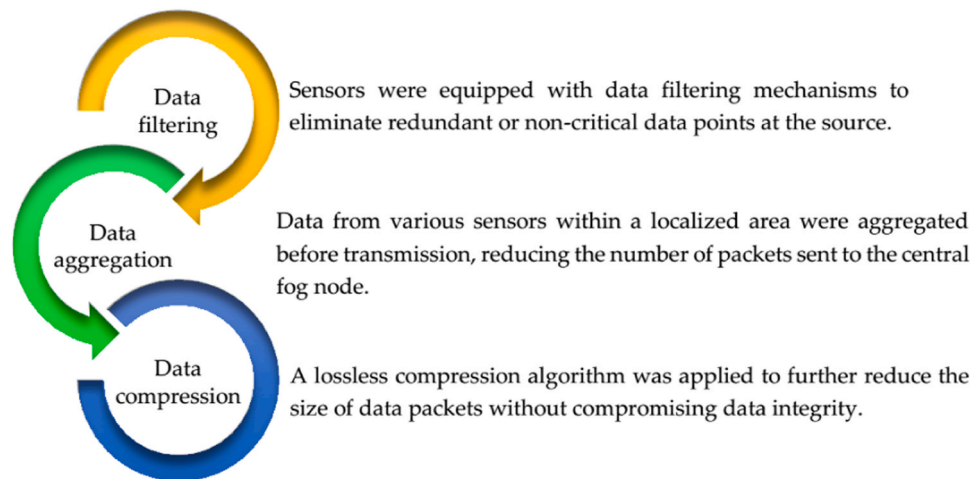


Fig. 2. Methodology for implementing aggregation and compression strategies for Industrial IoT within a fog computing environment.

any single route. It enhances reliability and prolongs network life (Kaur and Kaur, 2021).

- iv. *QoS-Aware routing*: Quality of Service (QoS)-aware routing takes into account not only energy efficiency but also application-specific requirements, ensuring data delivery meets performance goals (Faheem et al., 2017).
- v. *Geographic routing*: Geographic routing is based on node locations and minimizes energy consumption by forwarding data to the physically closest neighbour (Karagiannis et al., 2021).

Case study of energy-aware routing protocols for enhanced fog computing; resource-constrained areas with limited access to power sources such as the applications in a rural area (remote area) (Dewanta and Mambo, 2021). The rural areas with limited access to conventional power sources aimed to deploy an efficient and sustainable fog computing network for various applications, such as precision agriculture and environmental monitoring; which made it critical to optimize energy usage in the fog computing network of rural areas. Conventional routing protocols were not well-suited for this low-power, resource-constrained environment, and energy-efficient routing was a core component for the fog computing infrastructure in the rural area as well as essential to ensure the network's longevity. These protocols considered factors such as device energy levels, data transmission distances, and network topology when making routing decisions. Energy-aware routing was implemented as follows:

- i. *Reduced Packet Loss*: Energy-aware routing has shown substantial benefits in reducing packet loss compared to traditional routing approaches, primarily by optimizing energy utilization and avoiding the use of depleted or failing nodes. Metrics from case studies reveal that energy-aware routing protocols achieve a 30–50 % reduction in packet loss rates compared to traditional methods. For instance, a rural agricultural monitoring system utilizing energy-aware routing protocols demonstrated a packet loss reduction from 15 % to 7 %, resulting in a 53 % improvement. This decrease in packet loss directly contributes to energy savings by minimizing the need for retransmissions. Traditional routing protocols often experience higher energy consumption due to frequent re-sending of lost packets, consuming approximately 25 % more energy per transmitted packet in networks with higher loss rates. In contrast, energy-aware routing reduced overall network energy consumption by 20–35 % by ensuring more reliable initial transmissions and avoiding energy-draining retries. Moreover, the longevity of the network improved by 30–40 %, as fewer retransmissions alleviated the burden on nodes with constrained energy resources. Combining predictive analytics and AI-driven decision-making further optimized the selection of robust paths, preempting the involvement of unreliable nodes, and ensuring consistent communication even in challenging rural terrains (Haseeb et al., 2023).
- ii. *Data compression*: By reducing the volume of data transmitted across the network, compression techniques significantly decrease energy consumption during communication, with studies demonstrating energy savings of up to 30–50 % compared to traditional routing methods. Additionally, compression reduces data size by 40–70 %, leading to fewer packets transmitted, better bandwidth utilization (improvements of up to 50–60 %), and extended device lifespans by 20–30 %. For example, in a rural agricultural monitoring network, compression lowered the average energy required per kilobyte of data transmission from 1.2 Joules to 0.7 Joules, a 41.7 % reduction. Furthermore, network throughput increased by 45 %, and transmission latency decreased by 20–25 %, as fewer retransmissions were needed due to congestion. Techniques like Huffman coding and Lempel-Ziv ensure data integrity with typical compression ratios of 2:1–3:1, while lossy methods can achieve higher compression ratios for

non-critical data, amplifying energy savings. However, these benefits come with trade-offs, such as computational overhead that may offset savings if algorithms are not lightweight, and potential data quality loss in lossy methods. Compression at edge nodes, which preprocesses data before cloud transmission, further reduces network-level energy use by 35 %. Despite these challenges, data compression remains a key enabler for energy-efficient routing (Kaur and Kaur, 2021).

- iii. *Dynamic routing*: Dynamic routing has demonstrated significant benefits in rural IoT applications by optimizing path selection based on real-time conditions, such as energy availability, node status, and traffic load. The energy-aware dynamic routing can achieve energy savings of 20–40 % compared to static or traditional routing protocols, which often fail to adapt to the changing conditions of rural networks. For instance, in a rural environmental monitoring network, dynamic routing reduced the average energy consumed per packet transmission from 1.5 Joules to 0.9 Joules, yielding a 40 % reduction. Furthermore, the network's lifetime was extended by 35 %, as the workload was distributed more evenly across nodes, preventing energy depletion in specific areas. Dynamic routing also enhanced packet delivery rates by 20–30 %, as it avoided congested or low-energy nodes, leading to more reliable data transmission. In terms of latency, adaptive path adjustments resulted in a 15 % improvement, ensuring timely delivery of critical data such as weather alerts. Algorithms like Energy-Aware Geographic Routing (EAGR) and Ad-hoc On-Demand Distance Vector Routing (AODV) with energy metrics dynamically adjusted routes to minimize energy-intensive hops, achieving higher overall efficiency. Despite these advantages, implementing dynamic routing requires computational overhead at nodes to process real-time network conditions, which may marginally offset the energy savings if not optimized. However, incorporating lightweight AI models for predictive analysis and decision-making can further improve efficiency by preempting route failures and proactively balancing loads, solidifying dynamic routing as a key strategy for sustainable and energy-efficient networking in rural IoT deployments (Swaminathan et al., 2021).

The implementation of energy-aware routing protocols reduced the network's energy consumption by approximately 30 %, significantly extending the operational life of IoT edge devices and fog nodes, which allowed for consistent operation in areas with limited access to power sources. Moreover, the data was transmitted more efficiently, with fewer retransmissions and reduced packet loss.

In general, the energy-aware routing protocols in fog computing can lead to energy savings vary depending on factors such as network size and configuration, studies have demonstrated energy reductions ranging from 20 % to 40 % when compared to traditional routing protocols (Swaminathan et al., 2021). These savings result from optimized routing decisions that prioritize energy-efficient paths and minimize the number of hops, reducing energy consumption during data transmission. Achieving these energy savings requires careful consideration of device energy levels, dynamic routing adjustments, and the use of data compression techniques. Additionally, the selection of appropriate routing protocols and their configurations plays a pivotal role in maximizing energy efficiency. Continuous monitoring and adaptation to real-time conditions are essential for sustaining these energy savings while meeting the operational requirements of fog computing applications.

2.4. Energy-aware scheduling

Energy-aware scheduling for fog computing is instrumental in striking a balance between energy efficiency and application performance. The choice of scheduling technique depends on the specific

application’s energy constraints, requirements, and the need for real-time adaptation. These methodologies are indispensable in ensuring the longevity and reliability of fog computing systems (Wan et al., 2018; Ghanavati et al., 2020). Energy-aware scheduling methodologies focus on achieving energy savings through the following approaches (Matrouk and Alatoun, 2021):

- **Dynamic task assignment:** Tasks are allocated dynamically to available fog nodes based on their energy reserves and processing capabilities. High-energy nodes are prioritized for resource-intensive tasks.
- **Load balancing:** Scheduling algorithms distribute tasks evenly across fog nodes, preventing resource overuse and minimizing energy wastage. Load balancing ensures that no single node is overburdened.
- **Resource optimization:** Fog nodes and IoT edge devices adjust their resource usage based on their energy levels. Energy-efficient scheduling promotes the use of low-power states and resource allocation adjustments as needed.
- **Real-time adaptation:** Scheduling decisions are continuously adapted in response to changing conditions, such as fluctuations in energy availability, task priorities, and network congestion.

Energy-aware scheduling in fog computing encompasses several techniques, each tailored to specific scenarios and application requirements:

- i. **Priority-Based scheduling:** Priority-based scheduling is particularly valuable in fog computing scenarios where a mix of tasks with varying levels of importance and energy consumption coexist. This approach enables fog networks to balance energy efficiency with the performance requirements of essential applications, ultimately ensuring the sustainability and reliability of the system (Fahad et al., 2022). Choudhari et al (Choudhari et al., 2018). emphasize the significance of prioritizing tasks based on their criticality to applications, ensuring that essential services are not compromised, while energy-intensive tasks are carefully managed.
- ii. **Dynamic load balancing:** Dynamic load balancing is instrumental in fog computing environments where resource distribution can impact energy consumption and network performance. By continuously monitoring and adapting to real-time conditions, this approach ensures a balanced workload and efficient resource utilization, contributing to both energy savings and the longevity of the fog network (Singh et al., 2022a). Rehman et al (Rehman et al., 2020). introduced a dynamic load balancing approach that optimizes resource allocation and task distribution in fog computing environments. The study demonstrated the efficacy of this approach in conserving energy and ensuring even resource utilization.
- iii. **Energy-Aware task migration:** Energy-aware task Migration is a valuable technique in fog computing environments with resource-constrained fog nodes. By continuously monitoring resources and proactively relocating tasks, this approach contributes to balanced energy consumption, efficient resource utilization, and overall energy savings in the fog network (Jiang et al., 2020). Zhang et al (Zhang et al., 2020). investigated techniques for migrating tasks from energy-constrained nodes to those with sufficient energy reserves, contributing to energy conservation.
- iv. **Resource-Aware Scheduling:** Allocates resources such as CPU, memory, and network bandwidth based on energy-efficient rules and policies (Nesterenko et al., 2018).
- v. **Predictive scheduling:** Predictive scheduling with Machine Learning is especially valuable in fog computing environments with fluctuating workloads and varying energy constraints. By forecasting future energy availability and workload

requirements, this approach contributes to energy efficiency, prolongs the operational life of IoT edge devices and fog nodes, and ensures the reliability of fog computing services (Patman et al., 2018; Samann et al., 2021). Kuppusamy et al (Kuppusamy et al., 2022). employed predictive analytics and ML models to forecast workloads and energy availability, resulting in energy-efficient scheduling decisions and extended fog node lifespans.

Table 5 provides a comprehensive comparative summary, covering energy-aware scheduling, methodologies for energy conservation, as well as their respective advantages and limitations.

ML techniques have proven to be powerful tools for optimizing energy efficiency in fog computing by enabling intelligent resource management and task scheduling decisions. These ML-based approaches help schedule tasks to minimize energy consumption while still meeting QoS requirements. Genetic Algorithms (GAs) and Particle Swarm Optimization (PSO) are widely used to find near-optimal scheduling solutions by efficiently distributing tasks across fog nodes, leading to significant energy savings (Saad et al., 2024). However, these algorithms may struggle to provide optimal results in highly dynamic environments, limiting their effectiveness in real-time scenarios. Recurrent Neural Networks (RNNs) offer a more dynamic solution by predicting future workloads and scheduling tasks in real-time to prevent overloading specific fog nodes, thus ensuring energy-efficient processing (Ye et al., 2024). Despite their advantages, RNNs can be computationally expensive and require high processing power, making them less suitable for resource-constrained fog nodes in some cases.

Case study of energy-aware scheduling for enhanced fog computing; smart city (Dowlatshahi et al., 2021; Babar et al., 2021). A metropolitan smart city project sought to optimize its fog computing infrastructure for various applications, such as traffic management, public safety, and environmental monitoring. However, the smart city’s fog computing network faced challenges related to energy consumption, especially as the number of connected devices and data-intensive applications continued to grow. Optimizing energy utilization without compromising the performance of critical services was imperative. Energy-aware scheduling techniques were implemented to ensure the efficient use of resources and energy within the fog computing infrastructure. These techniques incorporated dynamic scheduling, load balancing, and resource allocation to minimize energy consumption (Babar et al., 2021). Energy-aware scheduling involves the following three (3) strategies as shown in Fig. 3. The smart city’s fog computing infrastructure achieved a 25 % reduction in energy consumption, leading to extended operational lifespans for IoT edge devices and fog nodes. Moreover, the dynamic scheduling and load balancing ensured that critical applications, such as traffic management and public safety, were not adversely

Table 5
Comparison of energy-aware scheduling techniques.

Technique	Methodology for Saving Energy	Advantages	Limitations
Priority-Based Scheduling	Real-time Adaptation	Ensures essential services, task prioritization	Limited impact on resource distribution
Dynamic Load Balancing	Load Balancing	Even resource distribution, energy savings	Complexity in dynamic routing
Energy-Aware Task Migration	Dynamic Task Assignment	Balances energy consumption, prolongs node life	Overhead due to task migration
Resource-Aware Scheduling	Resource Optimization	Efficient resource allocation, adapts to energy	Complex configuration, resource conflicts
Predictive Scheduling	Real-time Adaptation	Proactive energy conservation, predictive analytics	Requires historical data and models

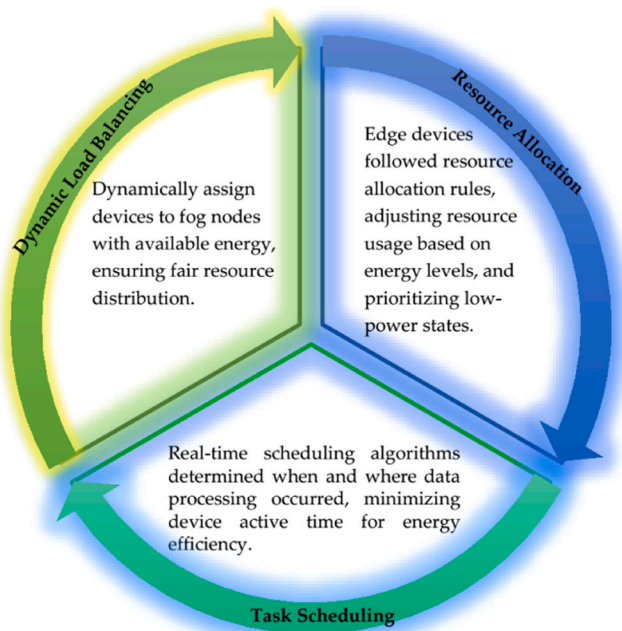


Fig. 3. Energy-aware scheduling strategies.

affected while non-essential tasks operated in low-power states. In addition, the energy-aware scheduling system was scalable, accommodating the growth of connected devices and new applications without compromising energy efficiency.

In general, studies have shown that energy consumption can be reduced by 20–30 % on average (Bambagini et al., 2016). These savings are achieved by optimizing the allocation of resources and tasks, ensuring that energy-intensive activities are carried out only when necessary. Considerations for achieving these energy savings include dynamic scheduling that responds to real-time conditions, load balancing to evenly distribute tasks among available resources, and prioritizing low-power states for devices whenever possible. The choice of scheduling algorithms and their configurations is crucial in balancing energy conservation with the performance requirements of fog computing applications. Continuous monitoring and adaptation to changing conditions are essential for maintaining energy efficiency over time. Notably, the exact amount of energy savings can vary depending on factors such as the scale of deployment and the specific scheduling algorithms employed.

2.5. Task offloading

Energy-aware task offloading is a critical paradigm within fog computing aimed at optimizing resource utilization and energy efficiency. This technique involves the strategic allocation and delegation of computational tasks among various computational nodes, including IoT edge devices, fog nodes, and cloud servers, based on energy consumption considerations. Task offloading is categorized into different types: computation offloading, data offloading, and joint computation-data offloading (Maray and Shuja, 2022). Computation offloading involves shifting computational tasks from resource-constrained devices to more powerful fog or cloud servers to enhance performance and conserve energy (Fig. 4). Data offloading focuses on transferring data from local devices to remote servers for processing, reducing local computational loads and energy consumption. Joint computation-data offloading combines both approaches, simultaneously offloading computational tasks and associated data for more efficient resource utilization. The benefits of energy-aware task offloading in fog computing encompass improved system performance, reduced energy consumption on

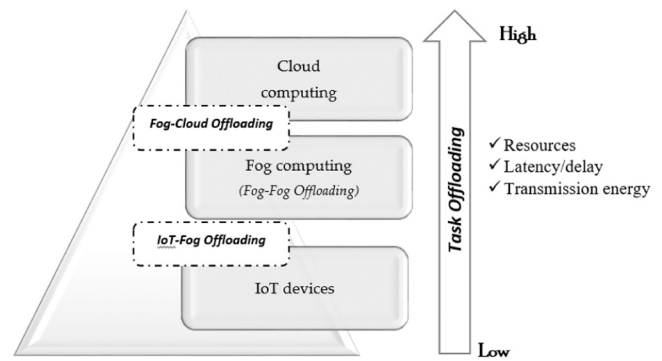


Fig. 4. Implementing task offloading methodology.

resource-constrained devices, minimized latency, and enhanced scalability (Kortoci et al., 2019). However, challenges such as network reliability, data security, and increased communication overhead pose limitations to effective task-offloading strategies in fog computing environments. Achieving an optimal balance between offloading decisions and local processing while considering energy constraints remains a significant challenge in realizing the full potential of energy-aware task offloading in fog computing.

Machine learning (ML) techniques have emerged as powerful tools for optimizing energy efficiency in fog computing environments by enabling intelligent resource management and task offloading (Shahidinejad and Ghobaei-Arani, 2020). Approaches such as Reinforcement Learning (RL) and Deep Learning (DL) have been applied to predict optimal task allocation, aiming to minimize energy consumption while maintaining system performance. RL models learn the best offloading policies based on various system states, including workload, latency, and energy consumption. This dynamic decision-making process helps prevent the over-utilization of fog nodes and reduces the need for frequent communication with cloud servers, significantly decreasing energy usage (Zhou et al., 2024). However, RL models face limitations in terms of high training complexity and scalability, which can hinder their effectiveness in large-scale fog environments. DL models, on the other hand, predict task resource requirements and node availability, allowing for efficient task offloading and execution by minimizing idle states and task reassignments (Khani et al., 2024). Despite these benefits, DL-based approaches require large datasets for accurate predictions and may struggle with real-time adaptability, particularly in highly dynamic fog computing scenarios.

Case study of energy-aware task offloading for enhanced fog computing; manufacturing facilities in remote areas (Jiang et al., 2018). A manufacturing facility in a remote location sought to optimize its operations by implementing fog computing technology, which enhances real-time monitoring, predictive maintenance, and automation. However, the primary challenge was to ensure energy-efficient data processing and analysis while maintaining the manufacturing processes' reliability and efficiency, especially since the facility relied on solar power and batteries for its energy needs. Energy-aware task offloading was critical to minimize the energy consumption of IoT edge devices and fog nodes. Energy-aware task offloading strategies were implemented to balance the computational load and energy utilization effectively. Thus, energy-aware task offloading not only optimized energy usage but also ensured the facility's long-term sustainability and economic viability in a remote location with limited energy resources. The energy-aware task offloading approach included the following components (Fig. 5). The facility experienced a 30 % reduction in energy consumption, which extended the lifespan of batteries and reduced the reliance on backup power sources; besides the manufacturing processes remained highly reliable and efficient, as critical tasks were consistently prioritized, which led to a decrease in energy consumption as well to reduced operational costs, making the facility more financially sustainable.



Fig. 5. Methodology for implementing energy-aware manufacturing facilities in remote areas within a fog computing environment.

In general, energy-aware task offloading in fog computing can reduce energy consumption ranging from 20 % to 40 %. The precise amount of energy savings varies based on the specific application, the scale of deployment, and the effectiveness of the task offloading strategies. Considerations critical to achieving these energy savings include accurate task profiling to identify high-priority and energy-intensive tasks, real-time monitoring of edge device energy levels, and dynamic task assignment to devices with sufficient energy reserves. Load balancing ensures that computational tasks are evenly distributed, preventing resource overuse. Predictive analytics play a key role in forecasting available energy, allowing for proactive scheduling of energy-intensive tasks during periods of high energy availability. By implementing these considerations, energy-aware task offloading optimizes energy consumption and contributes to the prolonged operational life of IoT edge devices and fog nodes, resulting in substantial energy savings.

2.6. Switching off/on strategy

Utilizing energy-saving strategies within fog computing, such as selectively powering off unused resources, effectively reduces energy consumption (Karimifshar et al., 2020). This method involves deactivating idle components like servers or storage units, optimizing resource utilization while minimizing power usage. Decisions on resource activation rely on factors like utilization patterns, with automated systems powering down resources during low activity periods (N. Toosi et al., 2022). Intelligent power management dynamically adjusts resource power states based on demand fluctuations, ensuring necessary computing capabilities are available while reducing energy consumption during low-demand periods. Methods introduced by authors in

(Haimour and Abu-Sharkh, 2019) include duty cycle control and passive wake-up triggered by external signals, requiring regulatory procedures to ensure availability. In IoT networks, fog nodes assist in controlling resource on/off mechanisms via Bluetooth Low Energy (BLE) interfaces, selectively activating based on geolocation estimations of device movement (Venanzi et al., 2019; Natgunanathan et al., 2023). However, in high-density scenarios, continuous BLE interface activation may impact energy efficiency. Careful management of resource switching is essential to prevent disruptions in critical operations or delays, requiring proper resource management and control mechanisms to swiftly bring powered-off resources back online when needed (Natgunanathan et al., 2023).

Case study of switching off/on unused resources for energy-aware fog computing; smart agriculture (Popli et al., 2021). A large agricultural operation aimed to optimize its crop yield, resource usage, and energy efficiency through the implementation of fog computing technology. The agricultural site relied on solar panels and battery storage, making it essential to maximize energy conservation. Thus, balancing real-time data processing with energy constraints was critical. The implementation of energy-aware resource management to dynamically switch off/on unused resources in fog nodes during periods of low activity is considered an effective solution in this case study. To maximize the advantages of the switching off/on technique, the following considerations should be taken into account:

- **Resource profiling:** Fog nodes were equipped with sensors and monitoring software to track resource usage, energy levels, and data processing capacity. This information was continuously updated.

- *Dynamic resource control:* When a fog node detected underutilized resources or low activity, it initiated a process to deactivate specific components, such as unused CPU cores or sensors, reducing energy consumption. This was based on predefined energy-activity thresholds.
- *Energy-Activity thresholds:* Thresholds were established to define acceptable energy levels and activity. If energy fell below a certain threshold or activity diminished, resource management was triggered.
- *Resource reactivation:* Inactive resources were reactivated when demand increased, ensuring the readiness of fog nodes for processing tasks.

The deployment of energy-aware resource management in a smart agricultural setting resulted in energy savings of around 15–20 % during low-activity periods. This not only extended the battery life but also reduced energy expenses. Moreover, the system maintained the effectiveness of real-time monitoring and control for irrigation, fertilization, and pest management processes even during high-activity phases, ultimately enhancing crop yield.

In general, the implementation of the switching off/on technique in fog computing can achieve energy savings ranging from 10 % to 40 %. The exact magnitude of energy savings depends on factors such as the scale of the fog network, the frequency of resource activation and deactivation, and the energy constraints in the environment. To achieve these energy savings, it is essential to consider carefully predefined energy-activity thresholds that trigger resource management, real-time monitoring of resource usage and activity levels, and the responsiveness of the system in reactivating resources when demand surges. By implementing these considerations, the switching off/on technique optimizes energy consumption, prolongs the operational life of fog nodes, and significantly reduces energy costs in fog computing environments.

While effective, resource switching on/off strategies introduce potential trade-offs, primarily in the form of latency when devices are powered back on to handle new tasks. Such delays can degrade the QoS, especially in time-sensitive applications like real-time monitoring, smart transportation, or healthcare systems. The root of these trade-offs lies in the time it takes for a powered-down component to become operational again. During this period, incoming IoT requests may experience delays (N. Toosi et al., 2022).

To mitigate these challenges, predictive analytics and AI-based models can play a transformative role. These tools leverage historical data, real-time monitoring, and advanced algorithms to forecast resource demands. For instance, (i) traffic prediction: AI models can analyze IoT traffic patterns to predict periods of high and low activity. During anticipated low-traffic periods, non-critical resources can be safely powered down. Conversely, resources can be pre-activated ahead of forecasted surges to minimize latency; (ii) workload distribution: By predicting workload fluctuations, tasks can be dynamically redirected to already active nodes, ensuring continuous service without delays caused by powering up dormant nodes; (iii) intelligent scheduling: AI-driven scheduling algorithms can prioritize tasks and decide which resources to activate based on their expected readiness time and energy efficiency. These predictive and intelligent approaches minimize the adverse effects of switching strategies, enabling fog computing systems to achieve significant energy savings while maintaining QoS. Future research in this area could focus on enhancing the accuracy of predictive models and developing lightweight AI algorithms that operate efficiently on IoT edge devices themselves, further optimizing resource utilization in energy-aware fog environments (Karimifshar et al., 2020).

2.7. Virtualization

Virtualization in fog computing refers to the abstraction of physical resources into virtual instances or entities, allowing multiple virtual environments to operate independently on the same physical hardware.

It enables the efficient utilization of resources, enhances flexibility, and aids in energy conservation within fog computing architectures. Moreover, dynamic allocation and reallocation of resources based on workload demands enable better utilization and energy efficiency (Avasalcai et al., 2020; Mukherjee et al., 2018). Several forms of virtualization will be addressed in the following paragraph. Moreover, Table 6 offers a comprehensive overview of the diverse virtualization techniques employed in fog computing. This table provides insights into their energy-saving methodologies, associated advantages, and potential limitations.

- *Server virtualization:* It involves partitioning a physical server into multiple virtual machines (VMs), allowing different applications or services to run independently. By consolidating workloads onto fewer physical servers, it optimizes resource utilization and reduces energy consumption by powering down underutilized servers.
- *Storage virtualization:* It abstracts physical storage resources, allowing the creation of virtual storage pools from multiple physical devices. Enables efficient allocation of storage resources, minimizing unused storage space and power consumption.
- *Application virtualization:* It abstracts application software from the underlying hardware, enabling applications to run in isolated environments. Increases flexibility and scalability by decoupling applications from the underlying hardware, facilitating more efficient resource utilization.
- *Network virtualization:* This technique abstracts network resources, enabling the creation of multiple virtual networks that share the same physical infrastructure. Efficiently manages network traffic, leading to optimal routing, which in turn minimizes energy consumption by reducing unnecessary data transmission.

The Hypervisor (shown in Fig. 6) acts as a crucial software link between the virtual machine (VM) and the host server, facilitating access between them within the virtualization infrastructure. It manages hardware resources, like CPU and memory, distributing them across different virtual environments, albeit with limited management features such as adjusting server capacity or initiating shutdowns (Durairaj and Kannan, 2014). When it comes to managing multiple hypervisors across physical servers, the VM provides comprehensive capabilities. Hypervisors typically operate on a single physical server, creating specific virtual images for that server. Once a virtualized system starts, the hypervisor states are stored in memory, assisted by hardware like the AMD Processor and Intel VMX. When a VM exits, the CPU transitions to the hypervisor’s execution context, operating on the stored memory data (Riddle and Chung, 2015). Kim et al (Kim and Park, 2015). explored various hypervisor types, such as Citrix Xenserver, VMware ESXi, KVM, and Hyper-V, proposing a VM placement scheme to address latency issues in VMs running on non-uniform memory access systems.

Table 6
Various virtualization techniques employed in fog computing.

Technique	Methodology for Saving Energy	Advantages	Limitations
Server	Consolidates workloads, optimizes resources	Efficient resource utilization, reduced hardware	Requires high initial investment, potential performance overhead
Network	Efficient traffic management	Better network optimization, reduced data traffic	Complexity in implementation, initial setup time
Storage	Efficient allocation of storage resources	Improved storage utilization, scalability	Potential data security risks, complex management
Application	Decouples applications from hardware	Enhanced flexibility, easier maintenance	Compatibility issues, potential performance impact

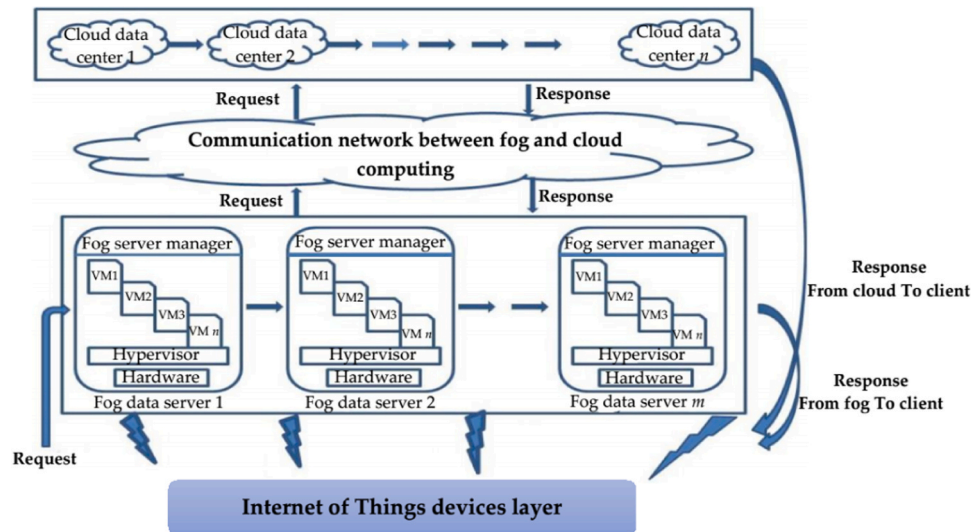


Fig. 6. Scheme of the Hypervisor mechanism process in computing environment.

Hypervisors fall into different categories like Para-Virtualization Hypervisor, Fully Virtualized Hypervisor, Hybrid Model Hypervisor, and Micro-Kernelized Design Hypervisor (Varrette et al., 2013).

A virtual disk (vDisk) is an integral component and is designed to streamline and expedite the relocation process of virtual server files. It accomplishes this by fragmenting a vDisk into smaller segments that mirror the structure of the virtual server's hard disk. This technique essentially consolidates the allocated hard drives for a virtual server, whether they are allocated before or after its creation. Each vDisk is stored as a file, or a series of files, in a format that adheres to the specifications of the underlying hypervisor. For instance, if the infrastructure uses Microsoft Hyper-V, the virtual disks are stored in the VHD file format. Conversely, when employing VMware ESX(i), the hard disks are stored in the VMDK file format (Lagar-Cavilla et al., 2009). In Fig. 7, an illustration showcases three distinct virtual servers VM A, VM B, and VM C. VM A is equipped with two virtual hard disks that are consolidated and stored as a single file. Meanwhile, VM B also comprises two hard disks; one of these disks is saved as a single file, whereas the other is split into multiple segments. On the other hand, VM C contains two hard disks, both of which are stored as split disks, signifying the segmentation of the vDisk into smaller parts for storage and management.

Case study of energy-aware virtualization for enhanced fog computing; smart city (Zhang, 2020; Javadzadeh and Rahmani, 2020). A smart city project aimed to optimize its public services, including

transportation, emergency response, and environmental monitoring, through fog computing technology. The city's infrastructure had strict energy constraints due to its commitment to sustainable energy sources, such as solar and wind power. The city required a solution that could efficiently allocate computational resources and minimize energy consumption in its fog network. Energy-aware virtualization was proposed and implemented to address the energy constraints while ensuring high-performance fog computing services. In addition, Energy-aware virtualization reinforced the city's commitment to sustainable energy practices. It allowed for the efficient delivery of critical public services while adhering to strict energy constraints. The energy-aware virtualization approach involved the following steps, as summarized in Fig. 8. The energy-aware virtualization implementation in smart cities as a study led to a 25 % reduction in energy consumption, aligning with sustainability objectives and reducing costs. Furthermore, critical public services like transportation monitoring and emergency response systems maintained high reliability and responsiveness, with ongoing prioritization of essential tasks.

In general, energy-aware virtualization in fog computing can achieve a reduction in energy consumption ranging from 20 % to 30 %. The precise amount of energy savings depends on the scale of deployment, the efficiency of virtualization management, and the energy constraints of the fog network. Key considerations for achieving these energy savings include accurate resource profiling of fog nodes and IoT edge devices, dynamic virtual task placement based on energy availability, real-time resource allocation, and continuous monitoring of energy consumption and workload. By implementing these considerations, energy-aware virtualization optimizes energy consumption, extends the operational life of fog nodes, and contributes to substantial energy savings in fog computing environments.

2.8. Low-power hardware implementations

Efficient utilization of hardware plays a pivotal role in fostering energy-aware Fog computing systems. Low power hardware constitutes a critical facet in this domain, focusing on reducing energy consumption while maintaining computational efficiency. This hardware is engineered with energy-efficient components, including processors, sensors, microcontrollers, and communication modules, optimized to perform tasks with minimal power consumption (Alsharif et al., 2023).

Processors and microcontrollers, often the heart of computational tasks, are engineered with low-power architectures and advanced sleep modes to minimize energy usage during idle periods (Adegbiya et al., 2017). These components leverage innovative design methodologies

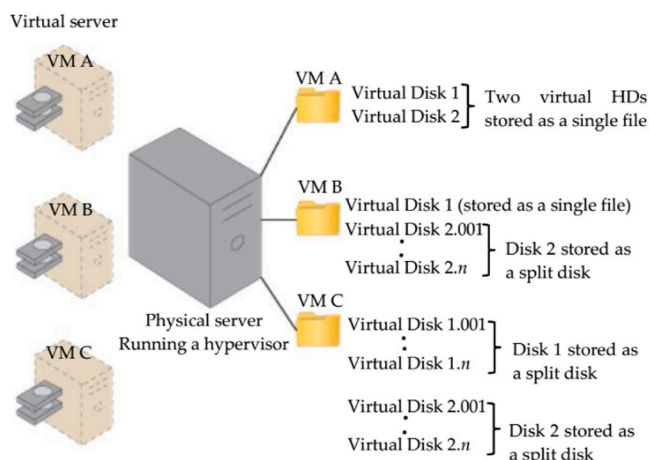


Fig. 7. Strategies employed in vDisk technology.

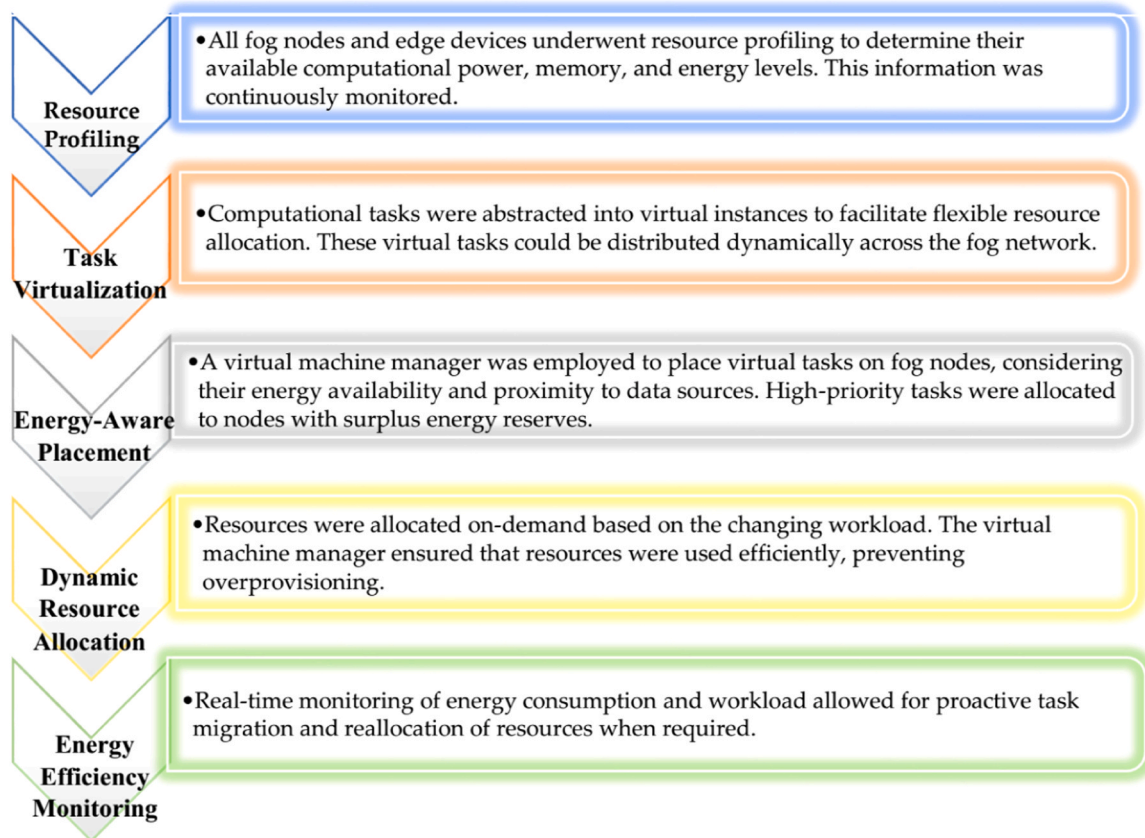


Fig. 8. The energy-aware virtualization effective steps.

like voltage scaling, clock gating, and power gating to regulate power supply and clock frequencies dynamically, aligning their performance with the processing demands (Chéour et al., 2020). Moreover, emphasis is placed on employing advanced fabrication techniques, such as nanometer-scale CMOS technology, to design processors and integrated circuits capable of processing tasks while conserving power (Alsharif et al., 2023). These technologies enable the integration of numerous functionalities into compact systems-on-chip (SoCs) while minimizing power consumption.

Communication modules are another crucial aspect of energy-aware hardware. They utilize low-power wireless protocols such as Zigbee, BLE, or LoRa, optimizing data transmission while consuming minimal energy (Moreno-Cruz et al., 2020). These protocols efficiently handle communication tasks, ensuring that devices remain in low-power modes for extended durations and reducing the overall energy footprint of the network.

Fig. 9 presents a comparison of power efficiency between multi-core and single-core processors across different operational stages. The performance at each stage depends on workload, frequency, and voltage settings. At lower operational stages, single-core processors (blue line) outperform multi-core processors (red line) in power efficiency. This is due to single-core processors' ease in entering low-power states during idle periods, significantly reducing power consumption. Conversely, multi-core processors often need at least one core active for system tasks, limiting their ability to achieve low-power states. However, as the operational stage increases, multi-core processors become more power-efficient. This shift occurs because the clock frequency of single-core processors increases linearly with the operational stage, leading to a quadratic rise in power consumption. In contrast, multi-core processors experience a less pronounced increase in clock frequency relative to the operational stage, resulting in a slower growth rate of power consumption (Alsharif et al., 2023).

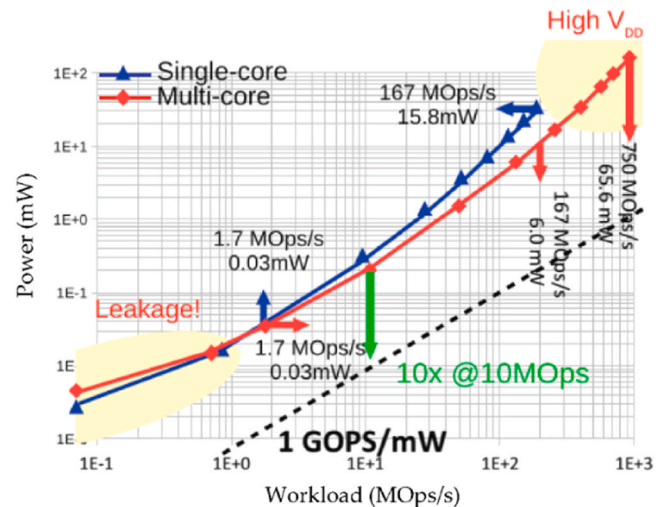


Fig. 9. A contrast in power efficiency between single-core and multi-core processors.

Dynamic Voltage and Frequency Scaling (DVFS) is a crucial power management technique in modern computing systems, enabling significant energy savings while balancing performance (Zidar et al., 2024). It works by dynamically adjusting the processor's voltage and frequency according to the workload. The core idea behind DVFS is to reduce power consumption by leveraging the quadratic relationship between voltage and power ($P(\text{power}) = C(\text{capacitance}) \times V^2(\text{voltage}) \times f(\text{frequency})$), meaning even a small reduction in voltage can lead to substantial energy savings (Hou et al., 2019). However, reducing voltage also limits the processor's maximum operating frequency,

requiring careful management to ensure that performance is not overly compromised. Implemented in most modern processors, DVFS is supported by hardware capabilities that offer multiple power states, allowing the system to select the most efficient state based on current demands. Operating systems and firmware play a vital role in managing these states, making real-time adjustments based on workload and thermal conditions (Ajmal et al., 2021). As technology advances, DVFS is expected to become more sophisticated, potentially integrating AI-driven algorithms to predict workload patterns more effectively and applying the technique on a per-core basis in multi-core processors for even finer control. Despite its advantages, DVFS presents challenges, including the risk of performance degradation if voltage and frequency are scaled down too aggressively, complex control algorithms needed to predict performance requirements accurately, and the physical limits of voltage reduction. Additionally, the transition between different voltage and frequency levels introduces latency, which can impact system performance if not managed properly (Hou et al., 2019). Despite the challenges, DVFS remains a fundamental technique in green computing, allowing systems to operate more efficiently under varying workloads and paving the way for more sustainable computing practices in the future.

Minimizing energy consumption in the computing environment involves optimizing the lighting system’s efficiency. In Fog computing, light sources like incandescent bulbs, compact fluorescent lightbulbs (CFLs), and light-emitting diodes (LEDs) are common. LEDs consume less energy while providing similar luminosity levels compared to CFLs and incandescent bulbs, as shown in Table 7, which compares luminosity measured in lm/W (lumens per watt) for these light sources. Numerous studies consistently support the superior energy efficiency of LEDs over CFLs and incandescent bulbs. For instance, LEDs demonstrated an energy efficiency of 100 lm/W in 2010, increasing to 200 lm/W by 2015 (Jou et al., 2022). Another study estimated LEDs’ potential annual energy savings to be around 22 % (Zhang et al., 2022). These findings emphasize the significant energy-saving advantages of LEDs compared to other lighting options.

Specific energy efficiency gains vary based on the hardware components and optimizations. Typically, employing low-power processors, sensors, communication modules, and microcontrollers can achieve notable energy reductions. For instance, transitioning from traditional processors to low-power variants may result in power savings of 20–40 % in computational tasks (Gomez et al., 2015). Low-power sensors equipped with efficient sleep modes and data aggregation techniques could offer energy savings ranging from 30 % to 50 % during sensing and transmission activities (Gharghan et al., 2016). Utilizing energy-efficient communication protocols such as BLE or Zigbee may lead to approximately 60 % less power consumption during data transmission compared to conventional protocols (Nikoukar et al., 2018). To attain these energy savings, considerations include optimizing hardware design, implementing advanced fabrication technologies, leveraging power management strategies, and employing efficient communication protocols. Additionally, maximizing the utilization of low-power sleep modes during idle states and minimizing unnecessary background operations play a crucial role in achieving significant energy reductions in Fog computing environments. The deployment of such low-power hardware across Fog computing infrastructure, if not only extends the operational life of devices by conserving energy but

also reduces the environmental impact associated with power consumption. Furthermore, by diminishing energy needs, these advancements contribute to cost reduction and foster the scalability of Fog computing systems. However, challenges persist in designing and implementing low-power hardware. Balancing energy efficiency with computational performance remains a significant challenge. Achieving optimal performance while minimizing energy consumption requires a delicate trade-off, often necessitating sophisticated design methodologies and trade-offs between hardware complexity and power efficiency.

2.9. Auto-scaling and resource provisioning

Auto-scaling and resource provisioning are foundational techniques in the realm of distributed computing systems, playing a pivotal role in optimizing energy efficiency by dynamically managing resource allocation in response to real-time demand (Shahidinejad et al., 2021b). Auto-scaling refers to the automatic adjustment of computing resources, such as CPU, memory, and storage, to match the current workload of an application or service. This capability is especially critical in environments like fog computing, where workloads can fluctuate significantly based on user activity, time of day, or specific events. For instance, during peak usage periods, auto-scaling can seamlessly add additional resources to maintain performance, ensuring that applications continue to run smoothly without degradation in user experience. Conversely, during off-peak hours or when the demand drops, the system can automatically scale down by decommissioning unnecessary resources, which directly reduces energy consumption. This dynamic adjustment prevents the common inefficiency of over-provisioning, where resources are kept active and consuming energy even when they are not fully utilized (Alharthi et al., 2024).

Resource provisioning complements auto-scaling by focusing on the strategic allocation and management of computing resources to various tasks, applications, or services within a distributed system (Ali and Zeebaree, 2024). Effective resource provisioning is essential for ensuring that each component of the system receives just the right amount of resources needed to meet its performance requirements, without over-allocating and thus wasting energy. This process involves accurately forecasting the resource needs based on workload patterns, historical data, and predictive algorithms, and then implementing strategies that optimize resource distribution. For example, in a data center managing multiple applications with varying resource demands, resource provisioning can ensure that high-priority tasks receive sufficient resources while less critical tasks are allocated resources more conservatively. This careful management not only maximizes resource utilization but also minimizes idle time, where resources are consuming energy without performing any useful work. When combined with auto-scaling, resource provisioning becomes even more powerful, enabling a responsive and energy-efficient infrastructure that can adapt in real-time to changing workloads. This synergy is particularly important in large-scale distributed systems, such as those found in data centers, where the scale of operations means that even small inefficiencies can lead to substantial increases in energy consumption and operational costs. The implementation of these techniques requires sophisticated control algorithms capable of making real-time decisions without introducing latency or instability in the system (Vahabi et al., 2023). Challenges such as avoiding excessive resource churn where resources are frequently added and removed must be carefully managed to ensure that the energy savings gained from auto-scaling and resource provisioning are not offset by the overhead associated with these adjustments.

ML techniques have become essential for optimizing energy efficiency in fog computing by enabling intelligent resource management and resource allocation. ML-based models can predict resource demands, balance loads across fog nodes, and dynamically scale resources to reduce energy waste. Support Vector Machines (SVMs) and Neural Networks are commonly used for this purpose, predicting future

Table 7
Comparing Luminosity between CFL, LED and Incandescent bulbs.

Lumens (Brightness)	Incandescent (Watts)	CFL (Watts)	LED (Watts)
400–500	40	8–12	6–7
650–850	60	13–18	7–10
1000–1400	75	18–22	12–13
1450 – 1700 +	100	23–30	14–20
2700 +	150	30–55	25–28

resource demand based on historical data. By avoiding the over-provisioning of resources, these models help reduce energy consumption (Aqib et al., 2023). However, their performance may decline in highly variable workloads, as prediction accuracy drops with irregular patterns. Clustering algorithms like K-means also contribute to energy efficiency by grouping tasks with similar resource requirements, which leads to more efficient task execution. This approach reduces energy consumption by minimizing the energy costs associated with frequent task switching (Abedpour et al., 2024). Nevertheless, clustering techniques can be less effective when dealing with real-time fluctuations in task requirements, limiting their adaptability in dynamic fog environments.

2.10. Energy harvesting techniques

This section delves into several renewable energy harvesting schemes tailored for fog computing, including solar, wind, thermal, and mechanical sources (Fig. 10). The primary goal of these harvesting systems is to provide a sustainable energy source for fog nodes. These schemes are often referred to as "ambient resource energy" due to their ability to tap into surrounding environmental resources for power generation. Furthermore, Table 8 presents a comprehensive summary of the energy harvesting techniques documented in the literature for fog computing.

2.10.1. Harvesting energy from solar sources

Solar energy stands out as one of the most abundant and easily accessible renewable energy sources, particularly during daylight hours, making it an ideal choice for energizing fog computing systems in remote and off-grid settings (Bozorgchenani et al., 2020; Singh and Sandhu, 2022). This transition away from conventional power sources not only bolsters the resilience of fog computing infrastructure but also enhances cost-effectiveness. Additionally, solar panels offer a sustainable energy solution with a minimal environmental impact, rendering them well-suited for environmentally sensitive areas (Bhutto et al., 2012; Kaura et al., 2024). Nevertheless, deploying a solar energy system involves certain considerations. Optimal site selection is paramount for maximizing energy capture, given that solar energy generation is intermittent. To ensure an uninterrupted power supply, especially during night-time or cloudy periods, the integration of energy storage

solutions is imperative. Furthermore, the efficiency of solar energy harvesting relies on factors like the type and quality of the solar panels employed (Alsharif et al., 2017). Fig. 11 shows the solar energy-powered harvesting system.

In (Abbas et al., 2014), the authors propose an analytical and distributed approach for managing energy resources in an unpredictable and uncontrollable environment. This approach becomes crucial as the distribution of energy relies on uncertain natural resources. In (Yang et al., 2013), an adaptive solar power prediction method is introduced, considering the volatility of weather conditions. Given the variability between sunny and rainy weather, accurate solar energy prediction becomes paramount for efficient energy harvesting. Authors in (Kosunalp, 2016) delve into the Q-learning solar energy prediction (QL-SEP) for energy harvesting, offering a method that aligns well with energy management due to its reliable predictions of non-controllable energy resources. The study compares various techniques, highlighting QL-SEP as the most effective in terms of prediction error ratios. Authors in (Samijayani et al., 2017) showcases the solar plate's performance under different weather conditions, emphasizing the significance of measuring solar plate quality for effective energy harvesting. In (Mustapha and Djenouri, 2017), an adaptive broadcast method based on energy harvesting is presented, utilizing Hidden Markov models and Baum Welch to optimize message transmission between base and sensor stations. In (Lee et al., 2010) incorporates energy management of solar energy harvesting in the network, employing packet reception rate algorithms for power savings. Reference (González et al., 2012) demonstrates sleep-wake-up strategies for solar energy systems, crucial for energy management in the face of the unpredictability of solar energy. In (Zhang et al., 2015) introduces an opportunistic duty cycle method for continuous solar energy harvesting, emphasizing the importance of duty cycles in energy savings. Reference (Joshi and Zhu, 2015) develops a structural health monitoring system utilizing solar energy, suitable for deployment in remote or inaccessible locations. Reference (Raghunathan et al., 2005) focuses on tracking techniques, such as surveillance, target tracking, and agriculture tracking, facilitated by solar energy systems, with a significant emphasis on outdoor environments.

2.10.2. Harvesting energy from wind sources

Wind energy represents another viable option for powering fog

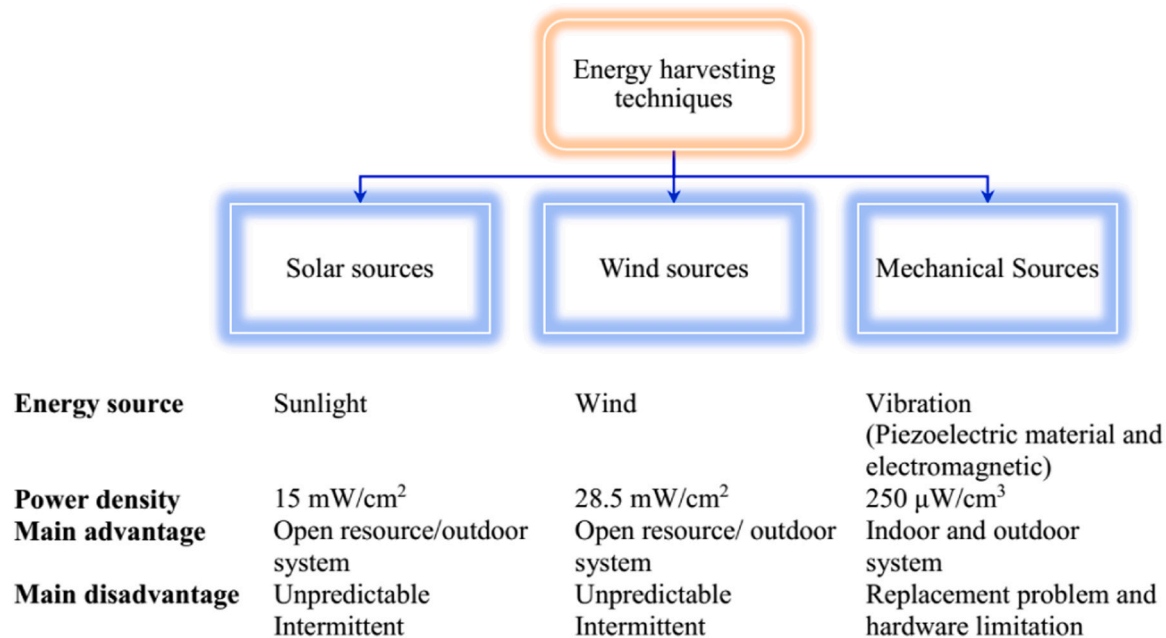


Fig. 10. Energy harvesting techniques.

Table 8
Energy harvesting techniques.

Energy Harvesting Technique	Reference	Approach/Idea	Contribution
Solar energy	(Abbas et al., 2014)	Analytical and distributed approach	Managing energy resources in an uncertain environment.
	(Yang et al., 2013)	Adaptive solar power prediction	Significant for efficient energy harvesting by considering weather volatility.
	(Kosunalp, 2016)	QL-SEP	Reliable predictions for non-controllable energy resources; superior to other methods in prediction error ratios.
	(Samijayani et al., 2017)	Solar plate performance analysis	Emphasis on measuring solar plate quality for effective energy harvesting.
	(Mustapha and Djenouri, 2017)	Adaptive broadcast method	Optimization of message transmission in base and sensor stations; uses Hidden Markov models and Baum Welch.
	(Lee et al., 2010)	Energy management of solar	Utilizes packet reception rate algorithm for power savings.
	(González et al., 2012)	Sleep-wake-up strategies	Crucial for managing the unpredictability of solar energy; compares with battery and solar radiation strategies.
	(Zhang et al., 2015)	Opportunistic duty cycle method	Ensures continuous solar energy harvesting with an emphasis on duty cycle importance.
	(Joshi and Zhu, 2015)	Structural health monitoring using solar energy	Deployment in remote locations with a focus on structural health monitoring.
	(Raghunathan et al., 2005)	Tracking techniques with solar energy	Surveillance, target tracking, and agriculture tracking facilitated by solar energy systems; outdoor environment emphasis.
Wind energy	(Kosunalp, 2017)	WEP algorithm	Predictive control of wind energy for effective resource management.
	(Zhao and Yang, 2017)	SCE circuit	Managing high-speed winds and temperature variations for wind energy utilization.
	(Aquino et al., 2017)	CFD	Mitigating adverse external wind effects in urban wind harvesting systems.

Table 8 (continued)

Energy Harvesting Technique	Reference	Approach/Idea	Contribution
Mechanical energy	(Jushi et al., 2016)	Outdoor wind energy improvement system	Utilizing industrial fans, anemometers, and MPPT circuits for energy transformation.
	(Wu et al., 2013)	MPPT circuit	Facilitating energy transformation and management in wind harvesting systems.
	(Sathiendran et al., 2014)	Buck-boost circuit for DC-to-DC conversion	Generating electric power for sensor nodes in wind energy networks.
	(Porcarelli et al., 2014)	DC-DC buck-boost regulator with MPPT	Integrating an adaptive hybrid voltage rectifier for efficient wind energy harvesting.
	(Iannacci, 2019)	Mechanical Vibration Energy Harvesting	Review of indoor/outdoor systems, component categorization, and ambient energy management.
	(Zhou et al., 2018)	Piezoelectric, Electromagnetic, Electrostatic, Thermoelectric Energy Harvesting	Categorization of system components based on various energy harvesting techniques.
	(Konstantopoulos et al., 2015)	Electric Potential Signals, Power Management, Signal Conditioning	Design aspects for efficient energy management.
	(Ruan et al., 2017)	Vibration Energy Harvester and Energy Storage Capacitor	Demonstration of energy storage within a vibration energy harvester.
	(Shaikh and Zeadally, 2016)	Low-Temperature Thermal Energy Harvesting	Exploration of a Zig-Bee wireless radiator and relevant thermal energy components.
	(Roseveare and Natarajan, 2013)	Prediction Methods for Energy Resource Management	Algorithm proposal for resource management and implementation of structural health monitoring.
	(Mo and Davidson, 2013)	Structural Health Monitoring, Piezoelectric, and Thermoelectric Energy Generation	Application of piezoelectric materials and thermoelectric generators for energy harvesting.
	(Abdal-Kadhim and Leong, 2017)	Power Management Circuit for Thermal Energy Harvesting	Conversion of heat energy into electrical energy using a DC-DC boost converter.
	(Hou and Tan, 2016)	Commercial Thermoelectric Module Integration	Implementation of a commercial thermoelectric module and sensor nodes for energy harvesting.

computing systems, especially in areas with consistent and adequate wind flow. This section explores the utilization of wind energy as an alternative energy harvesting source for fog computing infrastructure. Wind power offers several advantages, including its sustainability, as wind is a renewable resource. The deployment of wind turbines for energy generation in fog computing setups can reduce reliance on

Table 9
Summary of discussed energy-aware techniques for fog computing.

Energy-Aware Techniques	Methodology for Saving Energy	Considerations	Energy savings
Fog Computing Architecture	Placing computing resources closer to end devices, reducing data transmission distances and latency. It strategically distributes tasks across nodes based on proximity, workload, and resource availability.	- Careful cluster management. - Dynamic load balancing. - Effective resource management. - Efficient task offloading.	20 % ~ 30 %
Data Aggregation and Compression	Consolidating and condensing data packets before transmission to minimize the volume of transferred information. This technique reduces redundant data, minimizes transmission overheads, and optimizes bandwidth usage.	- Balance between data reduction and the application's requirements. - Effective algorithms for data filtering, aggregation, and compression.	10 % ~ 40 %
Routing Protocols	Optimize data transmission paths, reduce unnecessary hops, and select energy-efficient routes.	- Device energy levels. - Dynamic routing adjustments. - Data compression techniques.	20 % ~ 40 %
Scheduling	Optimizing the allocation and management of tasks, resources, and computations in Fog computing to minimize energy consumption and improve efficiency.	- Dynamic scheduling that responds to real-time conditions. - Load balancing to evenly distribute tasks among available resources. - Prioritizing low-power states for devices whenever possible.	20 % ~ 30 %
Task offloading	Dynamically allocating tasks based on available resources, employing proximity-based decisions, and optimizing communication protocols for efficient data transmission.	- Accurate task profiling to identify high-priority and energy-intensive tasks. - Real-time monitoring of edge device energy levels. - Dynamic task assignment to devices with sufficient energy reserves.	20 % ~ 40 %
Switching off/on	Switching off/on involves selectively powering down or activating resources based on their utilization, effectively reducing energy consumption in Fog computing.	- Resource profiling. - Dynamic resource control. - Energy-Activity thresholds. - Resource reactivation.	10 % ~ 40 %
Virtualization	Consolidating resources, running multiple virtual machines on a single physical server, and dynamically allocating resources based on demand, optimizing energy use.	- Accurate resource profiling of fog nodes and IoT edge devices. - Dynamic virtual task placement based on energy availability, real-time resource allocation, and continuous monitoring of energy consumption and workload.	20 % ~ 30 %

Table 9 (continued)

Energy-Aware Techniques	Methodology for Saving Energy	Considerations	Energy savings
Low-Power hardware	Deploying energy-efficient components, processors, and devices that consume minimal power.	- Implementing advanced fabrication technologies. - Leveraging power management strategies. - Employing efficient communication protocols.	20 % ~ 50 %
Energy harvesting	Energy harvesting in Fog computing captures ambient energy (e.g., solar, wind, mechanical) and converts it into electrical power to enhance energy efficiency.	- Deployment environment of solar panels and wind turbines. - Efficient energy storage solutions. - Responsive energy-aware fog node management.	20 % ~ 40 %

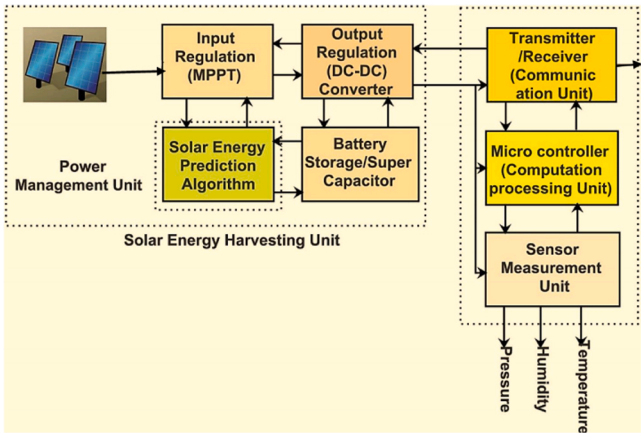


Fig. 11. Solar energy-powered harvesting system.

conventional power sources, enhancing the system’s resilience and cost-effectiveness (Okay and Ozdemir, 2016). However, the efficiency of wind energy harvesting relies heavily on the location and elevation of wind turbines. Additionally, intermittent wind patterns can pose challenges, necessitating the integration of energy storage solutions to ensure a continuous power supply. Despite these challenges, the harnessing of wind energy showcases the immense potential for providing sustainable power to fog computing systems, particularly in regions with favorable wind conditions (Ayar et al., 2023). Fig. 12 shows the wind energy-powered harvesting system.

Authors in (Kosunalp, 2017) introduce the Wind Energy Predictor (WEP) algorithm to manage wind energy’s unpredictability. Accurate wind prediction is crucial for efficient resource management due to wind’s frequent variability. Conversely, in (Zhao and Yang, 2017), emphasis is on handling high-speed winds using the Asynchronous Charge Extraction (SCE) circuit, crucial for various wind temperature scenarios. In (Aquino et al., 2017), a novel urban wind harvesting system uses Computational Fluid Dynamics (CFD) to counter external wind effects, enhancing efficiency. Additionally, (Jushi et al., 2016) showcases an outdoor wind energy system employing industrial fans, anemometers, PopWow platforms, and wind turbines. This system relies on power manager policies and the Maximum Power Transfer Tracking (MPTT) circuit (Wu et al., 2013). It includes a buck-boost circuit (Sathiendran et al., 2014) generating power for sensor nodes, integrating a DC-DC buck-boost regulator with MPPT (Porcarelli et al., 2014), utilizing an adaptive hybrid voltage rectifier and a small plastic micro-wind turbine.

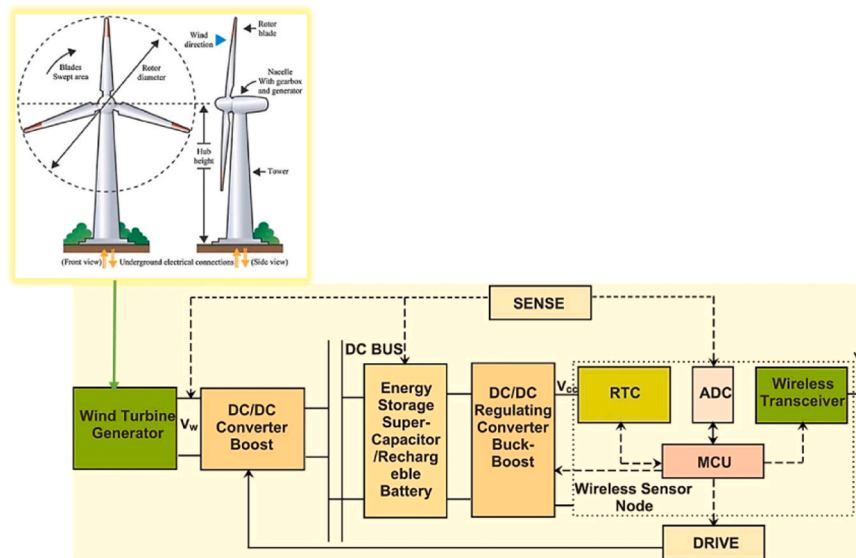


Fig. 12. Wind energy-powered harvesting system.

2.10.3. Harvesting energy from mechanical sources

Mechanical energy harvesting is a promising way to power Fog computing systems by converting mechanical energy (potential and kinetic) into electrical power through methods like vibrations, mechanical stress, and pressure. It includes three primary mechanisms: Piezoelectric, electrostatic, and electromagnetic. Additionally, other methods such as variable reluctance, magnetostrictive, magneto-electric, and Wiegand systems contribute to the diversity of mechanical energy harvesting approaches (Díez et al., 2018). Critical parameters integral to the design of mechanical energy harvesting systems include the conversion of mechanical motion, rechargeable batteries, super-capacitors, power management systems, and RF transmitters facilitating wireless communication within Fog computing environments (Dinulovic et al., 2015). The harnessing of mechanical energy offers a promising means to sustainably power Fog computing infrastructure, providing an alternative energy source and enhancing the systems' autonomy in various operational scenarios.

Herein is a breakdown with additional details for each technique used in mechanical energy harvesting. However, each of these mechanical energy harvesting techniques has its specific applications, advantages, and limitations. The selection of a particular method depends on factors such as available resources, energy requirements, environmental conditions, and the intended application within the Fog computing framework.

- **Piezoelectric energy harvesting:** Piezoelectricity involves the generation of electric charge in certain materials (like crystals or ceramics) when subjected to mechanical stress or vibrations. This charge can be harvested and converted into electrical energy. Piezoelectric materials offer advantages due to their high power density and reliability. They find applications in sensors, energy harvesters, and actuators.
- **Electrostatic energy harvesting:** Electrostatic energy harvesting operates by the movement of charged particles resulting from mechanical motion. It involves the separation of charges within a capacitor when subjected to mechanical stress. This technique requires lightweight and flexible materials and is suitable for low-power applications.
- **Electromagnetic energy harvesting:** Electromagnetic energy harvesting utilizes Faraday's law of electromagnetic induction to generate electric power. It involves the movement of a conductor through a magnetic field, inducing an electromotive force (EMF) and

subsequently generating electric power. This method is effective in environments with dynamic motion or vibrations.

- **Variable Reluctance Mechanism:** This technique relies on changes in magnetic reluctance within a circuit caused by mechanical movement. As the reluctance of the magnetic circuit varies due to motion, it induces changes in the magnetic field and generates electrical energy. Variable reluctance mechanisms are often used in rotating machinery or systems with intermittent motion.
- **Magnetostrictive energy harvesting:** Magnetostrictive materials change their shape in response to a magnetic field. This change in shape generates mechanical stress, which can be converted into electrical energy. These materials find applications in sensors, actuators, and energy harvesters.
- **Magneto-electric Mechanisms:** Magneto-electric devices utilize the coupling between magnetic and electric fields to generate electrical energy. This coupling allows for the conversion of magnetic energy into electric energy and vice versa, enabling bidirectional energy conversion.
- **Wiegand Mechanism:** The Wiegand effect involves a special type of wire made from a combination of magnetic and non-magnetic materials. When exposed to changing magnetic fields, this wire generates electrical pulses. These pulses are used to charge capacitors or batteries, making Wiegand systems suitable for low-power applications and sensors.

In (Iannacci, 2019), a detailed exploration of mechanical vibration energy harvesting covering indoor and outdoor systems is presented. Components include a beam holder, rotating host, piezoelectric beam, magnet holder, tip magnet, and driving magnet (Zhou et al., 2018). These elements are categorized into various energy harvesting methods like human interaction, heat, thermoelectric, pyroelectric, electromagnetic, electrostatic, and piezoelectric approaches. Management revolves around electric potential signals (Konstantopoulos et al., 2015), with key components such as power management, signal conditioning units, scatter radio units, and plant signal processing contributing to efficient energy harvesting. Additionally, the use of an energy storage capacitor as an example of a vibration energy harvester is highlighted (Ruan et al., 2017). In (Shaikh and Zeadally, 2016), a discussion focuses on a low-temperature thermal-based energy harvesting system with a Zig-Bee wireless radiator capable of 150 mW operation. This system includes thermoelectric structural materials, a DC-DC converter subsystem, automatic radiator valves (ZBARV), power management subsystems,

temperature distribution analog electric circuits, and thermal harvesting efficiency. Authors in (Roseveare and Natarajan, 2013) emphasize energy resource management prediction and propose an algorithm for controlling minimum increment space-time water filling. They also introduce structural health monitoring using piezoelectric materials and thermoelectric generators (Mo and Davidson, 2013). Furthermore, (Abdal-Kadhim and Leong, 2017) introduces a power management circuit for thermal energy harvesting, converting heat energy from temperature gradients into electrical energy using components like a DC-DC boost converter. Experimental results show maximum power generation of 50 mW in active mode and 15 mW in sleeping mode. Lastly, (Hou and Tan, 2016) implements a commercial thermoelectric module integrated with conversion circuits and sensor nodes for exploring thermoelectric energy harvesting.

Case study of energy harvesting for enhanced fog computing; remote environmental monitoring project. This case study exemplifies the benefits of energy harvesting in energy-aware fog computing, particularly in remote and off-grid environments. It not only ensures continuous data processing but also aligns with sustainable and cost-effective practices. A remote environmental monitoring project sought to establish a robust and sustainable fog computing infrastructure to gather and process data from various environmental sensors, such as weather stations (Froiz-Míguez et al., 2020), air quality sensors (Rani et al., 2021), and wildlife monitoring devices (Singh et al., 2022b). The project needed to ensure energy sustainability for fog nodes, where conventional power sources are not available in remote areas, requiring an energy-efficient solution. Energy harvesting techniques were implemented to harness renewable energy sources (solar panels, wind turbines, and hydroelectric microgenerators) and power the fog computing infrastructure efficiently. In addition, energy storage systems, such as advanced batteries and supercapacitors, were integrated to store excess energy for use during night-time or low-energy periods. Moreover, the fog nodes were equipped with energy-aware resource management software to adapt their operational modes based on energy availability. High-priority tasks were executed during periods of ample energy. The implementation of energy harvesting techniques led the project to significantly reduce operational costs, as it relied on renewable energy sources rather than conventional power supplies. However, the success of energy harvesting techniques hinged on effective site selection for solar panels and wind turbines, the efficiency of energy storage systems, and real-time energy monitoring. Additionally, energy-aware fog node

management was crucial for ensuring that critical tasks were executed during periods of energy abundance.

Energy harvesting for fog computing has the potential to yield energy savings ranging from 20–40 %. The actual energy savings depend on various factors, including the location and efficiency of energy harvesting systems, the energy storage capacity, and the specific energy constraints of the deployment environment. To achieve these energy savings, it is crucial to consider the strategic placement of solar panels and wind turbines for maximum energy capture, efficient energy storage solutions, and responsive energy-aware fog node management. By implementing these considerations, energy harvesting optimizes energy consumption, contributes to the sustainability of fog computing infrastructure, and reduces operational costs in off-grid and remote areas.

3. Potential future research directions

This section will explore the potential avenues for future research deduced from the prior discussion on energy-efficient techniques in fog computing (Fig. 13). Furthermore, it aims to introduce and deliberate on several research proposals geared towards captivating researchers' interests in this field.

3.1. AI-driven optimization

Leveraging AI and ML algorithms for smarter decision-making in task offloading, resource allocation, and energy management within Fog computing environments. Implementing predictive models can enhance efficiency in node selection, optimizing energy consumption while meeting latency constraints. Here are details on how AI-driven optimization can be applied:

- ✓ Task Offloading optimization: AI algorithms can analyze historical data patterns to predict workload demands and dynamically decide the optimal task offloading strategy. By considering factors like computational complexity, latency requirements, and energy consumption, AI can allocate tasks to Fog nodes or the cloud efficiently.
- ✓ Resource allocation: ML models can continuously monitor the performance of Fog nodes and dynamically allocate resources based on real-time demands. AI algorithms can predict resource requirements and adjust computing resources to optimize energy usage while meeting application needs.

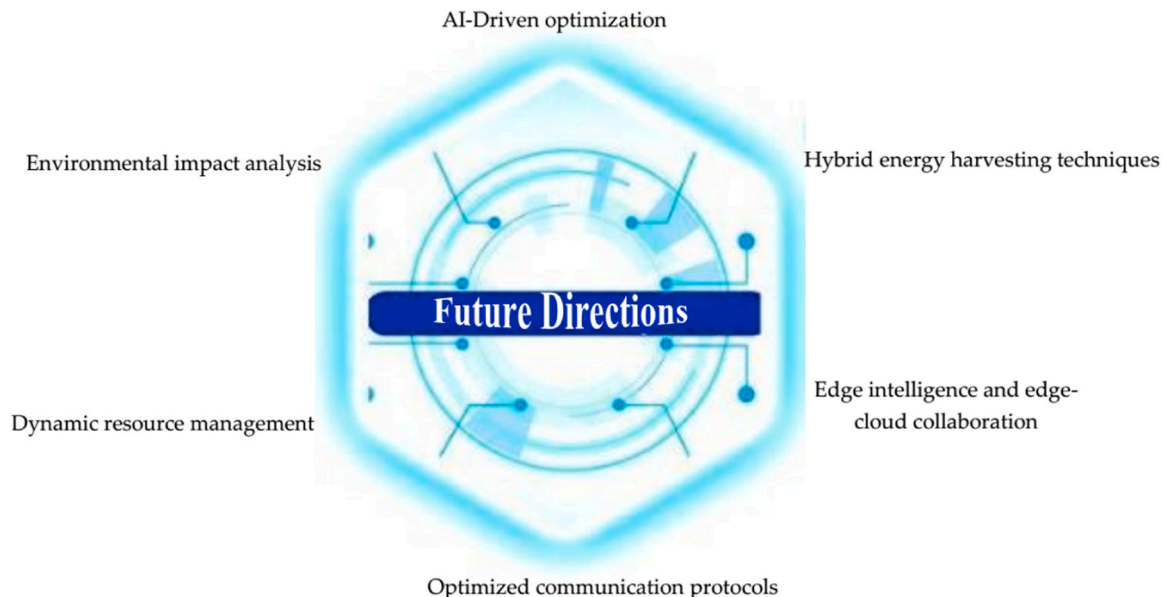


Fig. 13. Potential future research directions.

- ✓ **Energy-Aware routing:** AI-based routing protocols can intelligently select routes that minimize energy consumption by considering factors such as node energy levels, traffic patterns, and communication delays. These optimized routes can conserve energy during data transmission.
- ✓ **Predictive maintenance:** AI can predict the health and failure probability of Fog nodes by analyzing data on device performance and environmental conditions. Proactive maintenance schedules can be devised to replace or repair nodes before failures, reducing energy waste.

One of the open research propositions, warranting further investigation and scrutiny, is "AI-Driven Task Offloading Optimization for Improved Energy Efficiency in fog computing within Smart Cities," which might intrigue researchers. The proposed idea focuses on optimizing task-offloading strategies in a smart city environment. Utilizing historical data on application workloads, traffic patterns, and energy consumption, an AI-based model could predict future demands and optimize task distribution among Fog nodes. The study would analyze the efficiency gains in energy consumption, reduced latency, and improved performance in real-time applications such as traffic management or public safety systems. The methodology of the study would collect real-world data from various IoT sensors deployed across the smart city. ML models would analyze this data to predict future workloads and optimize task offloading strategies among Fog nodes. Performance metrics such as energy consumption, latency, and task completion times will be compared before and after AI-driven optimization.

3.2. Hybrid energy harvesting techniques

Hybrid energy harvesting for Energy-Aware Fog Computing involves integrating multiple energy-harvesting techniques to enhance the overall energy autonomy of Fog nodes. By combining various renewable sources such as solar, wind, kinetic, and thermal energy, this approach aims to mitigate the intermittency limitations of individual sources and achieve a more consistent and reliable power supply for Fog nodes in diverse environmental conditions.

- ✓ **Solar-Wind hybrid systems:** Integrating solar panels with small wind turbines can leverage both day-and-night and seasonal variations in energy availability. Solar panels generate energy during the day, while wind turbines can operate during night hours or in low-light conditions, thereby ensuring a continuous power supply.
- ✓ **Solar-Kinetic hybrid configurations:** Coupling solar panels with kinetic energy harvesting technologies, such as piezoelectric materials, allows the capture of mechanical energy from vibrations or movements in the environment. For instance, integrating piezoelectric materials into infrastructure or pavements can harness energy from pedestrian footfalls or vehicular movement along with solar energy during the day.
- ✓ **Wind-Thermal hybrid systems:** Combining wind turbines with thermal energy harvesting methods, like thermoelectric generators, can enhance energy capture in locations with consistent wind flow and temperature variations. Such integration allows simultaneous energy harvesting from wind movement and temperature differentials.

An open research proposal deserving further exploration and analysis involves "Hybrid Energy Harvesting for Smart Urban Infrastructure." In this case study, the focus would be on implementing hybrid energy harvesting systems within a smart city environment. For instance, integrating pedestrian walkways or street furniture with a combination of solar panels and kinetic energy harvesters, alongside strategically placing wind turbines on high-rise buildings or designated windy areas. This comprehensive setup aims to power various IoT devices and sensors dispersed across the city. The study would systematically monitor and

evaluate the collective energy output, efficiency, and reliability of the hybrid system under diverse weather conditions and seasonal variations. Moreover, it could delve into the exploration of intelligent algorithms or AI-driven optimization strategies. These strategies would dynamically manage and allocate the harvested energy, considering real-time demands and fluctuations in energy sources. Such an approach ensures optimal utilization and energy efficiency for Fog computing nodes and IoT devices integrated into the smart city infrastructure.

3.3. Edge intelligence and edge-cloud collaboration

Edge intelligence and edge-cloud collaboration in Energy-Aware Fog Computing involve leveraging the computing capabilities at the network edge, close to data sources, combined with cloud resources to enhance energy efficiency, reduce latency, and optimize computational tasks. Application of Edge Intelligence and Edge-Cloud Collaboration:

- ✓ **Localized data processing:** Edge intelligence involves deploying computational resources closer to data sources, enabling quick data analysis and decision-making at the edge. This minimizes data transmission to distant cloud servers, reducing energy consumption and latency.
- ✓ **Collaborative edge-cloud framework:** Integrating IoT edge devices with cloud resources facilitates an efficient division of computational tasks. Critical or time-sensitive tasks can be processed at the edge, while complex computations or resource-intensive tasks are offloaded to the cloud.
- ✓ **AI-driven optimization:** Implementing machine learning models or AI algorithms at the edge enables predictive analytics, anomaly detection, and local decision-making. It reduces the need for constant data transmission to the cloud for processing, conserving energy and bandwidth.

A promising research proposition that merits deeper exploration is centered on "Edge-Cloud Collaboration for Energy-Efficient Smart Monitoring Systems". The envisaged case study would concentrate on deploying an edge-cloud collaborative framework to monitor environmental facets, such as air quality, temperature, and traffic flow, using IoT sensors in an urban setting.

- **Edge implementation:** IoT edge devices installed across the city process local sensor data in real-time. They conduct initial data analysis, filtering, and basic analytics to detect immediate anomalies or critical events, minimizing data transmission to the cloud.
- **Edge-Cloud collaboration:** Data deemed less urgent or requiring further analysis is selectively offloaded to the cloud. This includes complex data modeling, long-term trend analysis, and predictive maintenance algorithms, optimizing the use of cloud resources.
- **AI-driven edge intelligence:** Implementing ML models at the edge allows devices to recognize patterns, forecast trends, and respond to local events without relying heavily on cloud processing. This minimizes energy consumption associated with continuous cloud interactions.

The study aims to assess the energy conservation, reduction in latency, and overall system efficacy attained through edge-cloud collaboration in handling diverse data streams. It will explore the influence on energy consumption and efficiency across different scenarios and varying loads within the smart city infrastructure. Additionally, the study may propose optimization methodologies like workload balancing algorithms or predictive models to further refine energy-aware fog computing in edge-cloud setups.

3.4. Optimized communication protocols

Optimized communication protocols are pivotal for enhancing

energy efficiency in Fog Computing. A research direction worth exploring further is "Dynamic Communication Protocols for Energy-Efficient Fog Computing Systems". A potential case study could focus on developing and implementing dynamic communication protocols tailored to different application scenarios within a smart city environment.

- ✓ **Application-Specific protocol design:** The study could delve into designing dynamic communication protocols optimized for various applications, such as smart transportation, healthcare, or environmental monitoring. For instance, in a transportation system, it could devise protocols prioritizing low-latency communication for real-time traffic monitoring and control.
- ✓ **Adaptive transmission modes:** Investigating protocols that dynamically adapt transmission modes based on data urgency and network conditions. These protocols could intelligently switch between high-bandwidth modes for urgent data and low-power modes during non-critical periods.
- ✓ **Context-Aware routing:** Developing routing protocols considering the context and changing network conditions. Utilizing AI-driven techniques or machine learning algorithms, these protocols could adapt routes based on traffic, device availability, and energy constraints.
- ✓ **IoT Device participation:** Proposing protocols that encourage IoT devices to enter sleep or low-power states when not actively transmitting data. Optimizing protocols for efficient wake-up strategies when data transmission is required.

A research proposal warranting deeper exploration revolves around simulating a sophisticated smart transportation system integrated with IoT sensors and devices tailored for traffic management. The research aims to design and implement dynamic communication protocols adept at adjusting to real-time traffic conditions. These protocols would facilitate optimized data transmission, ensuring traffic flow optimization and rapid incident detection within the system. An assessment of the study would include evaluating the achieved energy savings, reduction in communication overhead, and the overall effectiveness of the dynamic communication protocols across various applications within smart cities. Furthermore, the research could propose adaptive strategies or learning mechanisms to continually refine protocols and adapt to evolving environmental and network conditions for sustained enhancements.

3.5. Dynamic resource management

A research avenue deserving comprehensive investigation is "Dynamic Resource Management for Energy-Aware Fog Computing." This research will focus on developing resource management techniques that dynamically allocate computing resources in fog environments to optimize energy consumption and enhance overall efficiency. The proposed case study could involve deploying a smart urban infrastructure equipped with IoT devices and sensors for various applications like smart traffic management, environmental monitoring, and public safety.

- ✓ **Dynamic resource allocation:** The study would concentrate on devising algorithms that dynamically allocate computing resources to fog computing nodes based on real-time demands and resource availability. This includes dynamically adjusting CPU, memory, and storage allocations to match the varying workloads and energy constraints.
- ✓ **Intelligent workload balancing:** Implementing workload balancing strategies within the fog network to distribute tasks efficiently among nodes. The research would explore AI-driven techniques or machine learning models to predict workload variations and allocate tasks accordingly, optimizing resource utilization and energy efficiency.

- ✓ **Energy-Aware task offloading:** Developing strategies to offload tasks effectively among Fog nodes and Cloud servers. The goal is to minimize energy consumption by identifying the most energy-efficient processing location, considering latency constraints and available resources.

The case study would assess the effectiveness of these dynamic resource management techniques in achieving energy savings, reducing latency, and enhancing the overall performance of fog computing in a smart city environment. It would simulate various scenarios, such as sudden spikes in data demand or resource constraints, to validate the adaptability and efficiency of the proposed resource management strategies. Additionally, it could suggest predictive models or adaptive algorithms for continual refinement and better adaptation to changing environmental dynamics and workload conditions.

3.6. Environmental impact analysis

A promising area for exploration is "Environmental Impact Analysis for Energy-Aware Fog Computing." This research aims to quantify and mitigate the ecological footprint of Fog Computing systems in smart city environments. The proposed case study could involve deploying a comprehensive smart city infrastructure powered by fog computing and IoT devices, focusing on environmental monitoring, waste management, and energy optimization.

- ✓ **Eco-footprint assessment:** The study would evaluate the environmental impact of fog computing by assessing factors such as energy consumption, carbon emissions, and resource utilization. This assessment would compare the environmental benefits of fog computing against traditional cloud-based systems, considering factors like energy efficiency and reduced data transmission.
- ✓ **Life cycle analysis:** Analyzing the entire life cycle of fog computing infrastructure, from manufacturing and deployment to operation and decommissioning, to understand its environmental implications. This includes assessing the environmental cost of materials used in Fog devices and their end-of-life disposal.
- ✓ **Energy-Efficient practices:** Proposing energy-efficient strategies for fog computing systems, including using renewable energy sources, optimizing hardware design for reduced energy consumption, and employing energy-aware algorithms for task management and resource allocation.

The case study would involve extensive data collection and analysis to quantify the environmental impact of fog computing. It would assess the reduction in carbon footprint, energy savings, and environmental benefits achieved by implementing energy-aware practices. Additionally, it could suggest eco-friendly designs, such as using energy-efficient components, leveraging renewable energy sources, and adopting sustainable practices in fog computing infrastructure development and operation to minimize its environmental impact.

4. Conclusion

The culmination of this comprehensive investigation into energy-efficient Fog computing unveils critical insights and paves the way for future advancements in this domain. Through an in-depth analysis of various energy-saving techniques, architectures, and methodologies, this study underlines the significance of energy efficiency in Fog computing and its profound implications for the future of smart systems. The discussion on clustered and distributed architectures elucidates their respective advantages and challenges, emphasizing the need for efficient cluster head selection and workload balancing among sensor nodes. Furthermore, the exploration of energy-aware techniques such as data aggregation, compression, task offloading, and hybrid energy harvesting underscores their potential in mitigating energy consumption

and enhancing the sustainability of Fog computing networks. Novel concepts like AI-driven optimizations, edge intelligence, optimized communication protocols, and dynamic resource management emerge as promising avenues for future research, offering innovative ways to achieve higher energy efficiency in Fog Computing. These directions not only optimize resource utilization but also cater to the dynamic needs of modern smart city infrastructures. The practical case studies outlined in this study shed light on the real-world implications and challenges faced when implementing energy-aware strategies. These cases provide valuable insights into the feasibility, limitations, and benefits of deploying such techniques in diverse scenarios, fostering a deeper understanding of their applicability in practical settings. In the end, this study serves as a foundational compendium for researchers, practitioners, and stakeholders in the domain of Fog computing. It not only consolidates existing knowledge but also propels the field forward by presenting innovative pathways and highlighting the imperative role of energy-efficient strategies. The collective findings and proposed future directions underscore the significance of advancing energy-aware Fog computing for building sustainable and resilient smart systems in the near future.

CRediT authorship contribution statement

Kottakkaran Sooppy Nisar: Project administration, Investigation. **Manish Kumar Singla:** Supervision, Formal analysis. **Jyoti Gupta:** Software, Investigation. **Abu Jahid:** Investigation, Conceptualization. **Raju Kannadasan:** Validation, Resources. **Mohammed H. Alsharif:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Abdel-Haleem Abdel-Aty:** Methodology, Investigation. **Mun-Kyeom Kim:** Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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