Energy efficient fog computing for 6G enabled massive IoT: Recent trends and future opportunities

Usman Mahmood Malik, Muhammad Awais Javed, Sherali Zeadally, and Saif ul Islam

***Abstract*—Fog computing is a promising technology that can provide storage and computational services to future 6G networks. To support the massive Internet of Things (IoT) applications in 6G, fog computing will play a vital role. IoT devices and fog nodes have energy limitations and hence, energy-efficient techniques are needed for storage and computation services. We present an overview of massive IoT and 6G enabling technologies. We discuss different energy-related challenges that arise while using fog computing in 6G enabled massive IoT. We categorize different energy-efficient fog computing solutions for IoT and describe the recent work done in these categories. Finally, we discuss future opportunities and open challenges in designing energy-efficient techniques for fog computing in the future 6G massive IoT network.**

***Index Terms*—Energy-efficiency; fog computing; massive IoT; offloading; 6G**

I. INTRODUCTION

Wireless communication systems have advanced at a remarkable pace, revolutionizing the way humans and machines communicate. The explosive growth in the number of connected devices and the ever increasing demand for high data rate have been the main driving force for such evolutionary developments in the past decade. Currently deployment of Fifth Generation (5G) networks is under way, providing Gigahertz (GHz) connectivity to the end devices. This will ease our daily lives and will have significant impact on business efficiency [1].

Traditionally, it takes around ten years or so, before a cellular generation is replaced by a new generation. It is expected that 6G will be standardized and ready for deployment by 2030 for which the research focus has started to shift toward 6G communication systems [2], [3].

It is not yet clear what the advent of 6G will entail. However, from today's development pattern, it can be envisioned that the future societies will be highly connected involving billions of devices, increasingly digitized and data driven [4]–[28]. The road to 6G will see revolution in smart devices, smart technologies, artificial intelligence, remote tele-presence, autonomous vehicles and different types of data sources. Next generation connectivity will explore novel wireless technologies and innovative network architectures with very high data rates, ultra-low latency, and completely new services. The communication focus will evolve from ubiquitous connectivity to intelligent and automated connectivity [29].

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Advances in Internet of Things (IoT) technologies are paving the way for the emergence of 5G communication systems and will continue to shape the development of future 6G communication systems as well [30]. The number of connected devices are predicted to reach around 50 billion by 2030 [3]. All these devices will generate huge volumes of data traffic, transforming today's IoT into massive IoT of future [31]–[38]. Thus, future massive IoT networks will require high communication capacity to meet the data sharing demands of highly connected devices [39]–[45].

Massive IoT networks with 6G connectivity, employing intelligent learning techniques will be able to perform complex computations quickly, revolutionizing the user experience to near real time response [46]. Massive IoT networks will revolutionize our transportation, healthcare, agriculture and enterprise systems. Cities will become smarter with smart grid and inter connected electricity, water and gas connections [47], [48]. The devices will become context-aware and will be able to predict our needs. Vehicles will become autonomous and wearable devices will be extensively used making our lives safer and more comfortable [49]–[51].

With the increase in network capacity, network complexity also increases. 6G massive IoT will face several challenges which include heterogeneity, scalability, integration, interoperability, Quality of Service (QoS) provisioning, network capacity, network congestion and battery lifetime [4], [5], [7], [13], [26]. To meet these challenges, massive IoT will rely on intelligent learning techniques and rigorous deployment of fog and edge computing devices that are closer to the end devices [52]–[56]. Fog and edge computing devices will take the load off from cloud servers by performing computations closer to the end devices, thereby, improving computation latency [57]–[63]. Fog devices will intelligently incorporate idle/ spare resources of all available devices to further improve network efficiency [64], [65]. Computation resources of fog devices, edge devices and other available devices will be key in meeting requirements of highly demanding future applications.

6G devices will have high energy requirements because they will operate in higher frequency bands [66] but they will be made small in size to meet the versatile demands for future deployments, and they will typically have limited computation and power resources on board. Massive IoT networks will depend on fog and edge devices to perform computation tasks for edge devices, which are also constrained with limited communication, computation, storage and power resources.

TABLE I: Comparison of different applications and features provided by 5G and 6G

	5G	**6G**
Applications	enhanced Mobile Broadband (eMBB) Ultra-Reliable Low Latency Communications (URLLC) massive Machine Type Communications (mMTC)	Augmented reality Virtual reality Autonomous and connected drones and vehicles Intelligent and automated machines
Spectrum	sub-6 GHz millimeter wave	Tera Hz
Data rate	up to Giga bits per second	up to Tera bits per second
Latency	up to 1ms	$<$ 1ms
Reliability	99.9999%	99.99999%

Therefore, power consumption and energy efficiency will be critical challenges for 6G massive IoT networks and efficient resource utilization will be needed.

In this paper, we focus on recent trends on energy efficient techniques for fog computing based IoT networks. We present 6G enabling technologies and massive IoT applications. We highlight the energy challenges for 6G enabled massive IoT. Next, we present a survey of recent works done to achieve energy efficiency in fog computing empowered IoT. Finally, we present future opportunities and challenges for developing energy efficient solutions useful for 6G enabled massive IoT.

II. Related works

In this section, we present an overview of 6G networks, massive IoT and fog computing. We also present the motivations of this work.

A. 6G Networks

While 5G networks are still in the implementation phase, researchers have envisioned the next generation of mobile networks, namely 6G, that can support much higher data rates and many future applications [4], [5], [9], [12], [16]. Table I shows different applications and features of 5G and 6G communications. 5G communication focuses on delivering three main application services, namely, enhanced Mobile Broadband (eMBB), Ultra-Reliable Low Latency Communications (URLLC), and massive Machine Type Communications (mMTC). In contrast, 6G networks support applications such as augmented reality, virtual reality, autonomous and connected drones and vehicles, and intelligent and automated machines. All these applications require data rate of up to Terabits per second as compared to the data rate of Gigabits per second provided by 5G networks.

A key feature of 6G networks is the use of the Tera Hz spectrum. 5G networks are currently using sub-6GHz and millimeter wave spectrum. 6G networks will provide a latency of less than 1ms and a reliability of 99.99999% which will support pervasive connectivity and many future applications.

We present enabling technologies of 6G networks in Fig. 1. 6G will use physical layer technologies such as full duplex communication to enhance the communication capacity, and provide advanced channel estimation for efficient signal transmission and large intelligent surfaces to enable reliable data dissemination [8], [14], [20]. Moreover, 6G will use artificial intelligence to enable autonomous systems, distributed learning models to improve model accuracy, big data analytic for prediction and smart decision making, and realize intelligent edge, fog and cloud nodes [10], [11], [15], [21], [22], [24], [25].

Energy efficiency will be a key challenge for 6G networks [67]. One of the main reasons behind the need for enhanced energy requirements is the support for massive IoT applications [68]. Future network nodes including IoT devices and fog nodes will need to handle many tasks which will increase the energy consumption. Another energy related challenge for 6G networks is the use of Tera Hz communication which is a short range communication technology. While Tera Hz communication may provide higher data rates, it suffers from severe attenuation due to spreading loss and molecular absorption loss [69], [70].

6G networks will focus on energy efficient systems by providing low power communications, novel energy harvesting techniques, and energy efficient computing strategies. Massive IoT applications will also be supported by 6G networks by improving the accuracy of sensing and localization, and enhancing connectivity and computing capabilities. With all of the above features and technologies, 6G will be able to provide ubiquitous connectivity, Tera Hz communications, very high data rates, and ultra-low latency.

B. Massive IoT

Massive IoT refers to large scale connectivity of a large number of devices, sensors and machines [31], [32], [47], [48]. This classification of IoT is based on the number of connected devices and the amount of traffic generated by them. In the past decade, the number of devices connected to the Internet has significantly increased. In the next few years, this number will increase enormously requiring a robust network to support their connectivity [33], [34].

In massive IoT, the network density is very high, up to around 1 million devices per square kilometer [35], [36], [46]. This will result in a huge amount of data to be disseminated among devices, a large number of tasks to be performed, and massive amounts of information will need to be stored and big data analyzed [37], [38]. Thus, 6G and fog computing will be key enablers to support massive IoT applications.

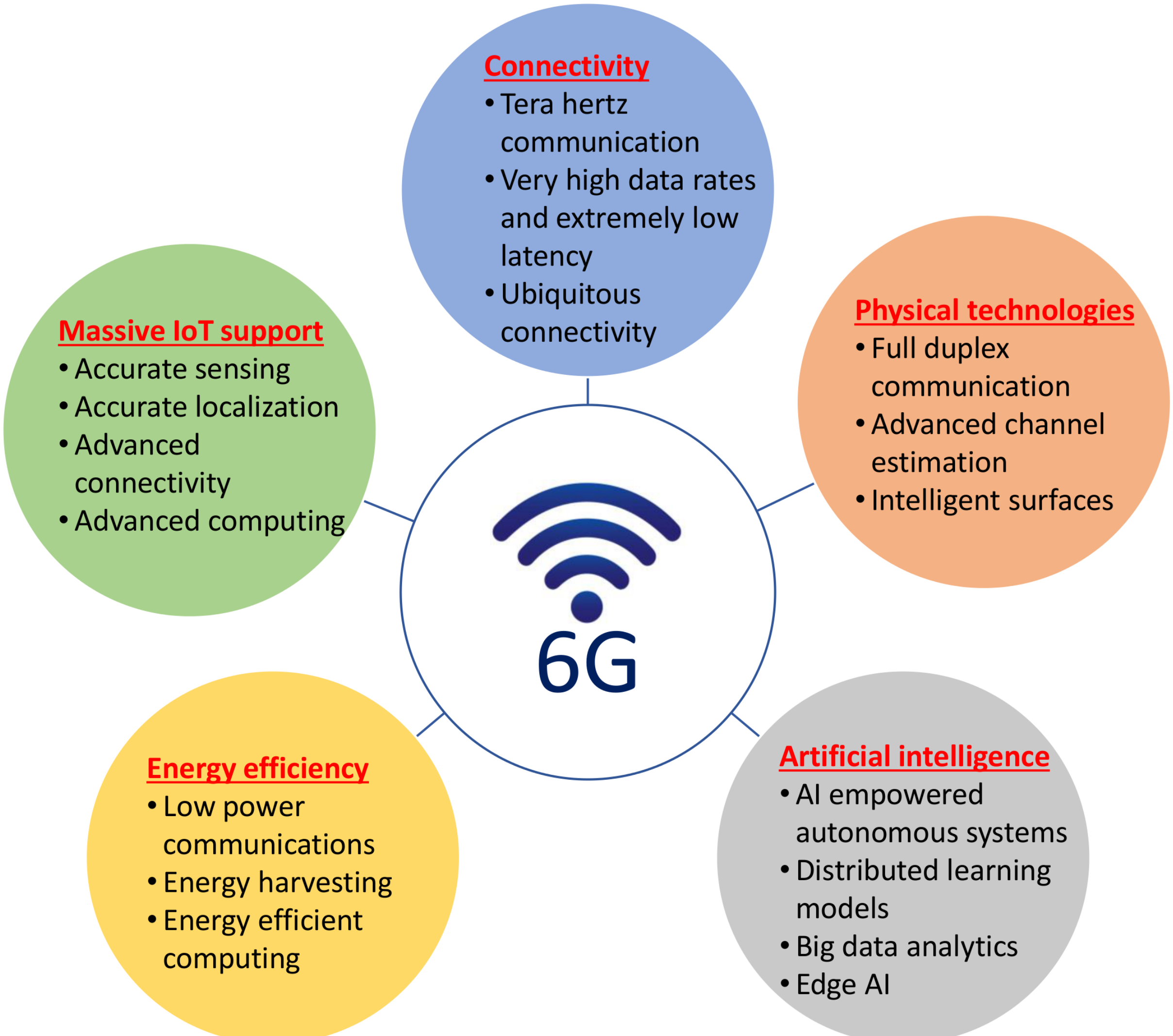

Fig. 1: Enabling technologies of 6G

C. Fog computing

Fog computing is a technology that enables edge devices to perform computation and storage operations closer to the edge [52]–[54]. By installing several fog nodes at various locations, devices are able to offload their tasks and cache data onto these nodes [55], [56], [71]. A major benefit of fog computing includes decentralized computing service as compared to the centralized computing offered by the cloud. Moreover, improved latency is achieved as data and tasks are accessed and analyzed near to the end devices [57], [58]. Fog computing also improves the usage of frequency spectrum and enhances the network capacity. It also has positive impact on application reliability as computation and storage capabilities are strengthened by the placement of fog nodes [59]–[61].

Fog computing will be a vital component of 6G enabled massive IoT. With the huge number of devices sharing data with each other along with a large number of applications, the assistance provided by fog nodes to the end devices in terms of computation and storage will be critical. Moreover, 6G communications will mostly utilize these fog nodes to enable ubiquitous connectivity and achieve very low latency. Several challenges pertaining to resource allocation, task offloading, energy efficiency, latency reduction, fairness and security will arise in this new paradigm of fog computing based 6G enabled massive IoT.

D. Motivation of our work

Research work on 6G massive IoT network has already started and future developments in this area is going to have a major impact on all aspects of our lives over the next few years. Future networks will be complex and will require energy that can provide power to billions of connected devices and it will not be feasible to change/recharge the batteries of so many devices on a regular basis. Thus, future networks and devices will have to be energy efficient.

Considering the importance of energy efficiency in future 6G networks, we focus on providing a survey of recent works in the field of energy efficient fog computing for IoT networks. We also present major challenges for achieving energy efficiency in fog computing based 6G enabled massive IoT. This paper attempts to provide recommendations to researchers working in the area of energy efficient fog computing.

Energy efficiency in IoT networks has been a popular research area and extensive research works have been undertaken in the areas of algorithms and techniques focusing on different levels and components of the network.

Various survey papers have been published on the topic of energy efficiency. Topics such as energy efficiency in IoT networks [72]–[77], cloud related aspects [78]–[83], certain level or component of the network [84]–[91], applications [92], [93], and techniques such as energy harvesting (EH) [94]–[102] have been extensively reviewed and summarized. However, to the best of our knowledge, we are the first to review the techniques for energy efficient fog computing in IoT networks.

Since a fog node is managing the resource allocation for end devices, therefore, we believe that resorting to energy efficient fog computing is one of the effective ways to make networks energy efficient. It will optimize energy consumption of the fog node along with the connected end devices that will help achieve energy efficiency. To the best of our knowledge, a survey paper on achieving energy efficiency by managing fog node operations has not yet been done. Therefore, in this paper, we focus on a survey of recent works done to achieve energy efficiency through fog nodes in the IoT networks.

Contributions of this work

We summarize the main contributions of this work as follows:

- To provide recommendations for future work, we focus on research works published after 2018.
- We consider only the techniques that use a fog node as the main contributor towards energy efficiency.
- We present a taxonomy and summary of energy aware fog computing techniques for IoT networks.
- We discuss Quality of Service (QoS) techniques for energy efficient fog computing in IoT.
- Finally, we identify and discuss future research directions for energy efficient fog computing in 6G enabled massive IoT.

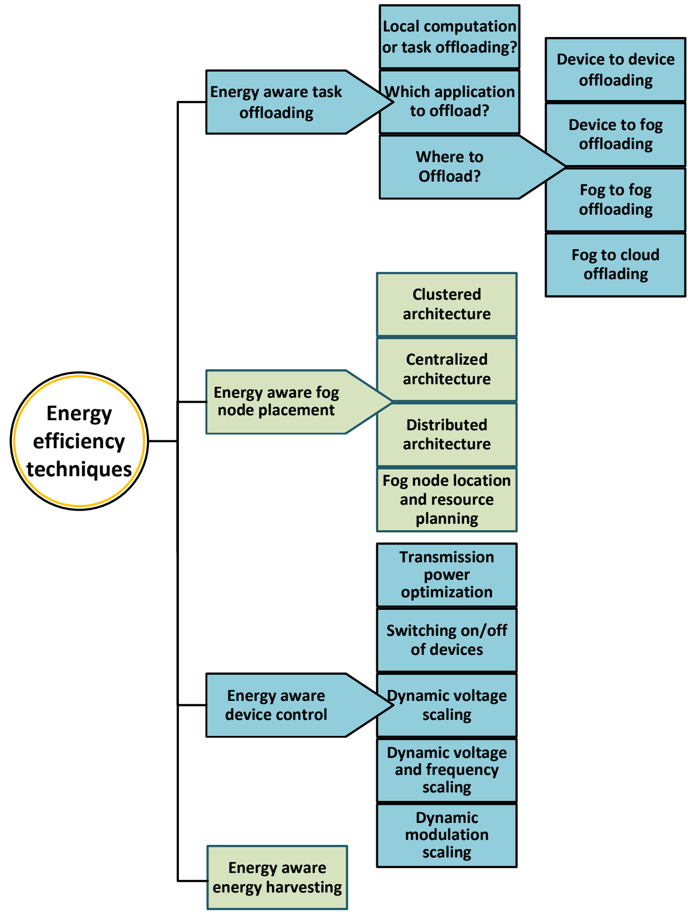

Fig. 2: Energy aware techniques for energy efficient fog computing in IoT

III. Energy aware techniques for energy efficient fog computing in IoT

In this section, we present a survey of recent trends and work done in the field of energy aware techniques for energy efficient fog computing in IoT. We classify the current techniques in this area into four (4) categories as Fig. 2 shows.

A. *Energy aware task offloading*

Most devices in the IoT network are battery powered with limited computational and communication resources. These devices can thus serve a limited number of tasks at a limited speed. Applications on the other hand are becoming increasingly computationally extensive, requiring low latencies and real-time responses. These applications can quickly deplete the power resources of the devices, rendering them unavailable in the network for further use. Extending the lifetime of IoT devices by conserving/ boosting device energy to make full use of their finite energy supplies remains a significant challenge [103].

One effective way to conserve the power supply of any device (we call these devices as local devices) is to get assistance from other devices (we call these devices as task helper nodes such as fog nodes) to perform tasks on behalf of that local device. This process of resource sharing among devices to carry out tasks is called the process of task offloading. When a device offloads a task, it conserves its computational energy at the cost of energy required to communicate data between the local device and the task helper nodes. The tasks are broken down into local and offloaded components, where local tasks are performed by the local device itself and offloaded tasks are performed by the task helper nodes. The task offloading decision is managed by various types of resource allocation techniques.

Time constraint or maximum time limit for task completion is the main consideration when making task offloading decisions. Task offloading has contradictory effects on latency and task execution time. On one side, it improves the latency through parallel processing of the task by both the local devices and the task helper nodes, while on the other side, it adds communication latency through up-link transmission of the task to the task helper nodes and down-link transmission of the result to the local device. The total latency of the task depends on the following factors [104]:

- *Pre-task offloading time:* Data processing time in the local device.
- *Task uplink time:* Time required to send the task information from the local device to the task helper node.
- *Wait time at the task helper node:* The difference between the time when the task computation is started at the task helper node and the time when the task reached the task helper node.
- *Task computation time:* Time taken by the task helper node to compute the task.
- *Task result communication time:* Time taken to communicate the results of the task from the task helper node to the local device.
- *Post-processing time:* Time taken by the local device to make decisions based on post processing of the task.

In the context of fog computing, energy efficiency can be best achieved through energy aware task offloading which optimally transfers the computation tasks to the idle/ underutilized task helper nodes in order to achieve energy efficiency at the network level. To achieve energy aware task offloading, the following three decisions need to be carefully made: (1) local computing or task offloading?, (2) which application to offload?, and (3) where to offload?

1) Local computing or task offloading?: When a computation task is offloaded from a local device to another task helper device, it significantly reduces its energy consumption. But since task offloading requires data communication between the local device and the task helper device, it results in additional energy consumption and communication latency. Consequently, a task shall be offloaded to the task helper device only when the energy consumption and latency can be reduced.

Local computing is generally preferred over task offloading under the following conditions: (1) The latency of task offloading exceeds the permissible threshold limit for task execution. (2) The estimated energy conservation by task offloading is lower than the transmission energy required to transmit the offloaded task. (3) All the energy required for task execution is provided through energy harvesting.

Local devices can partially or completely offload their task. This division into local component and offloaded component depends on latency requirements of the task and energy consumed by the device in transmitting the offloaded component.

2) Which application to offload?: Applications may be composed of multiple services and offloading may not benefit all services equally. Therefore, the services that can benefit from offloading need to be identified and only those services should be offloaded [105].

In [106], the authors have recommended that applications can be grouped according to their latency and computation requirements to pre-determine the location where they should be processed. This grouping assists in making quick and energy aware task offloading decisions. Table II presents the recommended classification of applications. Applications with low computational and high latency requirements may be offloaded near to the local devices i.e., on other IoT devices or fog nodes. In contrast, tasks which have high computational and low latency requirements may be offloaded to the fog nodes or the cloud servers.

Application requirements	**Offload location**
Low computational and high latency requirements	Device/ fog
High computational and high latency requirements	Fog only
High computational and low latency requirements	Fog/ cloud
Varying computational and low latency requirements	Flexible (device/ fog/ cloud)

TABLE II: Recommended offload locations based on application requirements

3) Where to offload?: A typical IoT network consists of geographically distributed heterogeneous devices with different computation, communication, storage and power resources. A device performs its own task first and participates in resource sharing only if it has spare resources. The decision on which task helper node to choose for task offloading is a critical one because it has major implications on latency and energy efficiency of the network. Current works in this area focus on developing techniques that choose from the multiple geographically distributed task helper nodes available to achieve energy efficiency while meeting the latency requirements of applications.

IoT resources are arranged in a hierarchical order: cloud, fog nodes and edge devices (maximum to minimum resources). Different task offloading options that can be considered include [115]:-

- Device-to-device offloading.
- Device-to-fog offloading.
- Fog-to-fog offloading.
- Fog-to-cloud offloading.

Fig. 3 summarizes the objectives of these task offloading options. We describe each of task offloading options in the following subsections. Table III presents recent works related to energy aware task offloading.

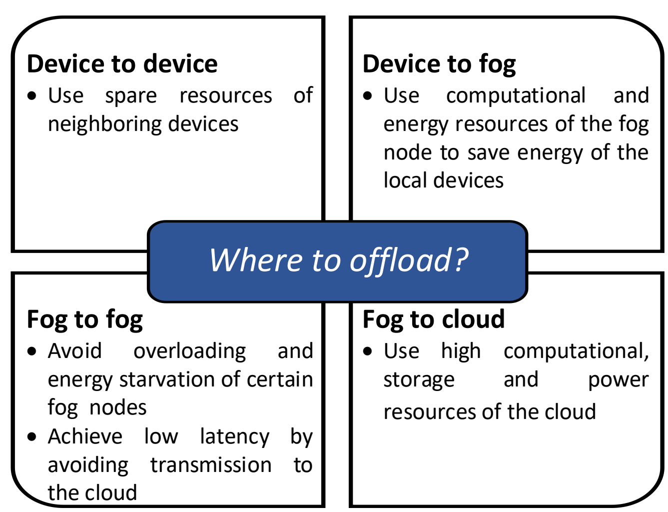

Fig. 3: Objectives of task offloading options

TABLE III: Research work - Energy aware task offloading

Year	Reference	D2D	Device-to-fog	Fog-to-fog	Fog-to-cloud	Key idea	Energy efficiency target	Performance metric
2019	Sun et al. [107]	Y	Y	-	-	Sensor nodes in a cluster cooperate with each other in relaying their tasks to the fog node to conserve transmission energy	Sensor nodes	Node state distribution Node remaining energy Network life-time
2020	Wang et al. [108]	Y	Y	-	-	Sensor nodes in a cluster cooperate with each other in relaying their tasks to the fog node to conserve transmission energy	Sensor nodes Mobile fog node	Energy consumed Delay Network life-time
2020	Huang et al. [109]	-	Y	-	-	Finds willing fog node to perform task for local devices	IoT devices	Energy consumed Queue stability
2019	Zu et al. [110]	-	Y	Y	-	Uses graph theory to pair a task fog node with a helper fog node	Fog node	Energy consumed
2019	Zhang et al. [111]	-	Y	Y	-	Finds a suitable helper fog node for a task node, employing fairness	Fog node	Energy consumed Fairness among fog nodes Offloading service feasibility
2019	Kim et al. [112]	-	Y	-	Y	Proposed task model based on occurrence probability (popularity) of tasks	User equipment Fog node	Energy consumed Service time
2020	Hou et al. [113]	-	Y	-	Y	Define strategies to employ/ utilize fog node resources to achieve energy efficiency and load balancing in data centers	Data center	Energy efficiency Queue length
2019	Jiang et al. [104]	-	Y	Y	Y	Chooses offload device that has: Minimal workload Maximum remaining energy	Overall energy reduction	Energy consumed Ratio of tasks completed on time to the total number of tasks generated
2020	Gai et al. [114]	-	Y	Y	Y	Proposed optimization of pre-stored task allocation table in fog servers to find optimal device/ location for task offloading	Overall energy reduction	Energy consumed Time taken to generate allocation plan

'Y': supported
'-': not supported

a) Device-to-device offloading. The basic idea of Device-to-Device (D2D) task offloading is to utilize spare computational and energy resources of other local devices in the proximity instead of always uploading/ downloading data to/ from remote nodes such as fog and cloud [116]. Since these devices are in the neighborhood, therefore, data transmission between these devices take place on direct communication link requiring little transmission energy which conserves energy.

Only those computationally intensive tasks, which are beyond the capability of devices to complete within the delay threshold, are offloaded to fog node or to the cloud. D2D task offloading significantly reduces the routing overhead and computing burden on the fog/ cloud layer. The policy to offer some sort of an incentive against the sharing of resources can be implemented to encourage D2D task offloading.

In [107], [108], the authors used a D2D task offloading scheme to achieve energy efficiency in the sensor nodes that are small in size and have limited power supply. These sensor nodes do not have enough energy to transmit directly to the fog node. Thus, they assist each other in conserving transmission energy. These sensor nodes are arranged in clusters to better manage the assignment of tasks and the flow of information. The cooperative transmission scheme enables the sensor nodes to collect data from each other and efficiently transmit this data to the fog node.

b) Device-to-fog offloading. Local devices have to offload their computation tasks to remote computing systems such as fog or cloud to offset their limitations of restricted computational and power resources. This task offloading conserves their energy resources and makes them available for longer time in the network [117]. Cloud servers are located far away and offloading tasks directly from the local device to the cloud will not be feasible because it would consume a large amount of transmission energy and it would also lead to unacceptable task processing delay. On the other hand, fog nodes are located in close proximity to the end devices and offloading tasks to the fog nodes will conserve transmission energy and also improve latency. Thus, for the local devices, task offloading to the fog nodes is a better choice. For example, in [104], [109], [112], [114], the authors have used a device-to-fog offloading scheme to conserve energy resources of the devices.

c) Fog-to-fog offloading. When fog nodes have high workload such as computing a heavy task or when there is a need to conserve their energy, tasks from fog nodes can be offloaded either vertically to the cloud or horizontally to the neighboring fog nodes [118].

As the distance between the fog nodes and the cloud is typically large, vertical offloading consumes a high amount of transmission energy and also increases latency which may not be feasible for time sensitive applications [119]. On the contrary if the task is offloaded horizontally, there are many available task helper fog nodes. However, their capability as compared to the cloud, will be low. Their strength in numbers make up for their deficiency in their capabilities and when utilized properly, neighboring fog nodes can effectively relieve each other and handle large tasks. Since neighboring fog nodes are in close proximity compared to the cloud, such task offloading will conserve transmission energy and will also improve latency.

Zu et al. [110] used fog-to-fog offloading to conserve energy resources of fog nodes. They used the many-to-one matching technique of graph theory to choose a helper fog node that has best channel conditions and least energy consumption. The task fog node that has some task to offload broadcasts the task's information. The helper fog nodes that have spare/idle resources, upon receiving multiple task requests, make their priority list of task fog nodes to serve based on the best channel conditions. They propose their services to the first task fog node in the list. Based on the proposals received, the task fog node selects the helper fog node that provides the best energy conservation. The process continues until all matches are done.

Zhang et al. [111] utilizes fog-to-fog offloading to conserve the energy resources of fog nodes. The task fog node also considers the power source of the helper fog node during the task offloading decision. A small amount of task is offloaded to the battery powered fog nodes to ensure their availability in the network for long time.

Selecting the right fog node to offload the task remains an important challenge. Dynamic and context aware mechanisms need to be developed to select the most appropriate fog node for offloading without affecting other functionalities of the fog node. Complex and sophisticated resource management is needed to achieve energy efficiency. Vertical offloading could be an option and the decision is made in real time to decide where to offload the task. Fog-to-fog offloading not only takes the load off from the cloud but also reduces the load on the transmission links between the fog and the cloud.

d) Fog-to-cloud offloading. Cloud servers are equipped with high computation, storage, and power resources. In traditional IoT networks, cloud servers are designed to receive tasks from all kinds of devices for processing. Intermediate processing devices such as fog nodes and edge devices are placed to assist cloud servers and overcome the disadvantage of the large distance between the cloud servers and the local devices. Fog nodes offload their tasks to the cloud and use the additional computational, storage and energy resources of the cloud [105].

Kim et al. [112] considered device-to-fog and fog-to-cloud offloading options to conserve computation energy. The authors used task popularity to decide where to offload the task. The task popularity is determined using a probabilistic model based on the frequency of initiated tasks. Popular tasks and those with low latency requirements are offloaded to the fog and rest are offloaded to the cloud.

Hou et al. [113] developed strategies to achieve energy efficiency and load balancing in data centers. The authors discussed different types of utilization strategies of fog nodes wherein the fog node computation can take the load off the data center. When the fog node assists data centers in task computation, it makes data centers more energy efficient and also alleviates the load on them.

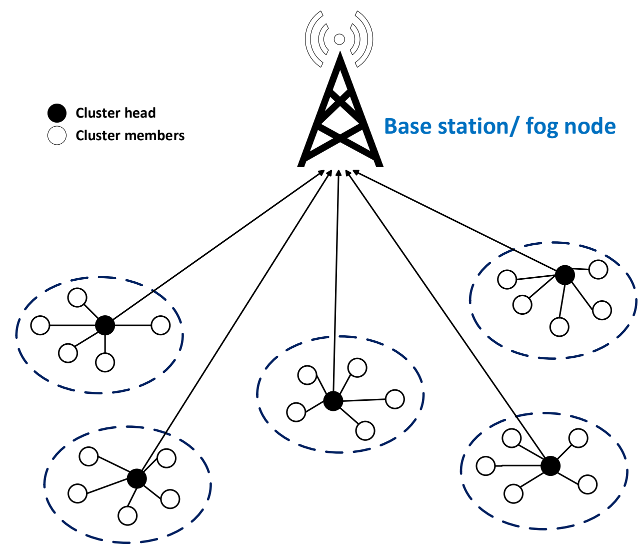

Fig. 4: Clustered architecture

Jiang et al. [104] also considered both task offloading options, offload to fog or offload to cloud. However, when doing fog-to-fog offloading, the authors selected the helper fog node based on minimum workload and maximum remaining energy.

Gai et al. [114] considered a heterogeneous network in which task offloading tables are pre-stored in the fog server. When a task comes, an initial sub-optimal task allocation plan is formulated from these pre-stored tables using greedy algorithms. The sub-optimal task allocation plan is optimized using shifting algorithms. The shifting algorithm iteratively replaces selected computation units with non-selected units to find the optimal selection which conserves energy while remaining within the time constraints.

B. Energy aware fog node placement

Fog based IoT network has no standard architecture to date and is best represented using a layered representation. Researchers have proposed three, four and six layers for the fog architecture [125]. The most commonly used is the three-layer architecture i.e., cloud layer, fog layer, and edge layer. Resources in these layers are hierarchically distributed with cloud servers having the most resources, fog nodes having medium resources that act like an extension of cloud layer, and edge devices having least resources.

For the purpose of energy conservation in fog based IoT network, three types of node placement architectures can be considered which are: (a) Clustered architecture, (b) Centralized architecture. and (c) Distributed architecture. We describe these architectures in the following subsections. Table IV summarizes the recent works related to fog node placement.

TABLE IV: Research work - Energy aware fog node placement

Year	Reference	Fog node placement	Key idea	Energy efficiency target	Performance metric
2019	Sun et al. [107]	Clustered architecture	Clustered architecture for transmission energy efficiency	Sensor nodes	Node state distribution Node remaining energy Network lifetime
2020	Khalifeh et al. [120]	Clustered architecture	Finds the optimal location of cluster head with respect to cluster members to reduce transmission path loss	Sensor node (cluster head)	Energy consumed by the network Path loss for all connections
2019	Rafi et al. [121]	Clustered architecture	Optimizes internal communication of a cluster Finds best relay for each sensor node using Dijkstra's algorithm	Sensor nodes	Node remaining energy Number of rounds
2020	Wang et al. [108]	Clustered architecture	Finds the shortest path for mobile fog node using minimum spanning tree	Sensor nodes Mobile fog nodes	Energy consumed Delay Network life-time
2019	Omoniwa et al. [122]	Clustered architecture	Uses mobile/ static fog node relay Proposed an outage minimization technique to ensure longevity of relay fog nodes	Relay fog nodes	Outage probability Convergence behavior Optimal selection of fog relays
2019	Bozorgchenani, [123]	Centralized and distributed architecture	Proposed a centralized and decentralized architecture and compares them under different scenarios	Overall energy reduction	Task delay Node energy consumed Network life-time
2020	Silva et al. [106]	Distributed architecture	Finds optimal location and resource configuration of fog node to provide maximum service to end users	User equipment	Energy consumed Proportion of applications processed at fog node
2020	Wu et al. [124]	Distributed architecture	Forward deployment of computing servers	Overall energy reduction	Latency Load balance

1) Clustered architecture: Clustering is one of the most popular techniques used in Wireless Sensor Networks (WSNs) for energy efficient communications. In clustered WSN, sensor nodes are grouped in clusters of different sizes. This size depends upon sensor node's location, density and distance from the base station/ fog node. In each cluster, a resourceful sensor node is elected as the cluster head that controls communication flow within the cluster. All cluster member sensor nodes sense their data and forward it to the cluster head which aggregates the data and sends it to the base station/ fog node.

Fig. 4 shows a typical clustered WSN. Clustering reduces transmission emissions in the cluster which helps in achieving energy efficiency by saving the energy of power-constrained sensor nodes. Clustering also offers benefits such as scalability, improved network life, reduced routing delay, decreased network traffic, and channel access management. The main challenges in a clustered WSN environment include: (a) Selection of the cluster head (b) and the routing scheme used to collect data from the cluster head.

Sun et al. [107] distributes sensor nodes in clusters and selects a cluster head in each cluster that has energy more than the cluster's average energy. The cluster head controls all communication within the cluster and acts as an aggregation point for all data generated in the cluster. To improve energy efficiency, a communication hierarchy is established among cluster heads based on their distance from the main fog node. A few of the cluster heads are selected as relays to assist in data transmission to the main fog node. The relay cluster head closest to the main fog node is selected as the network relay cluster head. The data passes from the sensor nodes, cluster head, relay cluster head and network relay cluster head to the main fog node. The cluster head is switched in each round to balance the energy consumed among sensor nodes.

Khalifeh et al. [120] distributes sensor nodes in clusters and selects a cluster head in each cluster based on its remaining energy. In a cluster, sensor nodes take turns to become a cluster head to have fair energy consumption among them. Since sensor nodes are randomly distributed in a cluster, therefore, they have different path losses among them. There may be a case where the selected cluster head has bad channel conditions with most of the cluster members, which result in high transmission loss to the sensor nodes. To overcome this problem, the fog node finds the optimal location of the cluster head with respect to the other nodes location in the cluster, such that the path loss between the cluster head and the nodes is minimized. The selected cluster head moves to that location to achieve energy efficiency in the cluster.

Rafi et al. [121] distributes sensors in clusters wherein each sensor node has equal possibility of becoming a cluster head. A sensor node is selected as a cluster head if it has the lowest workload. Cluster members cannot communicate outside the cluster directly and send their data to the cluster head using other sensor nodes in the cluster as relay. The authors optimized internal communications of a cluster using the Dijkstra's algorithm to select the best relay for each sensor node to reach the cluster head. Dijkstra's algorithm considers the weights assigned to each link to choose relay sensor node for each sensor node and establishes load balancing by selecting the sensor node with low load, when the weights of two sensor nodes are similar.

Wang et al. [108] distributed sensor nodes in clusters and used fog nodes to elect the node with the highest credibility as the cluster head in each cluster. This credibility is based on node's residual energy and error free communication history. All cluster members communicate only with the cluster head which aggregates their data and communicates with the mobile fog node. To further improve energy efficiency, the authors used the Minimum Spanning Tree (MST) method to find the shortest path to traverse all the cluster heads. The mobile fog node traverses the MST path and collects data from all the cluster head sensors, aggregates it and sends it to the cloud.

Omoniwa et al. [122] used fixed and mobile fog nodes in the IoT network to act as relays between sensor nodes and main fog node/ cloud servers. When a sensor node needs to transmit data, a relay fog node is selected that best reduces its transmission energy. The mobile relay fog node adjusts its location to further increase the transmission's energy efficiency. The relay fog nodes assist sensor nodes in conserving their transmission energy but they also have power constraints for which the authors developed the outage minimization technique. In this technique, the relay fog nodes are selected according to their remaining energy and workload. The relay fog nodes with less remaining energy and high workload are given less tasks to ensure availability of relay fog nodes in the network for long time period. This also ensure fairness in their use.

2) Centralized and distributed architecture: Bozorgchenani et al. [123] used clustered approach to propose a centralized and a distributed architecture for task offloading among fog nodes to optimize both energy and time. The proposed architectures are evaluated to find their advantages and disadvantages under different scenarios.

All fog nodes are distributed into two layers based on their power supplies. Battery operated fog nodes are considered in the fog node layer, and fixed fog nodes having electric power supply are considered in the Fog Access Point (F-AP) layer as Fig. 5 shows.

Fog nodes in the fog node layer are further classified as High Power Fog Nodes (HPFNs) and Low Power Fog Nodes (LPFNs) based on their energy levels. This classification is updated every time a new task is generated to consider the most updated remaining energy level of fog nodes. LPFNs offload their tasks to HPFNs and F-AP based on the architecture used:

a) Centralized architecture. The clustered architecture approach is used to develop the centralized architecture which consists of a Fog Cluster Head (FCH) and Fog Cluster Members (FCM). FCH is selected from the group of HPFNs and FCMs are selected from the group of LPFNs, considering their geographical locations and distances from the FCH. In the proposed architecture, FCMs can only be served by its FCH or associated F-AP under the following two policies:-

(i) Policy 1. In this policy, only the fog node layer is used and all processing takes place within the cluster. FCMs are served by their FCHs and the role of fog nodes keeps on changing depending upon their remaining energy levels.
(ii) Policy 2. In this policy, both fog nodes and F-APs layers are used for task offloading. FCMs can offload their tasks to the associated FCH and to the associated F-APs. Likewise, FCHs can also partially offload their tasks to the associated F-AP.

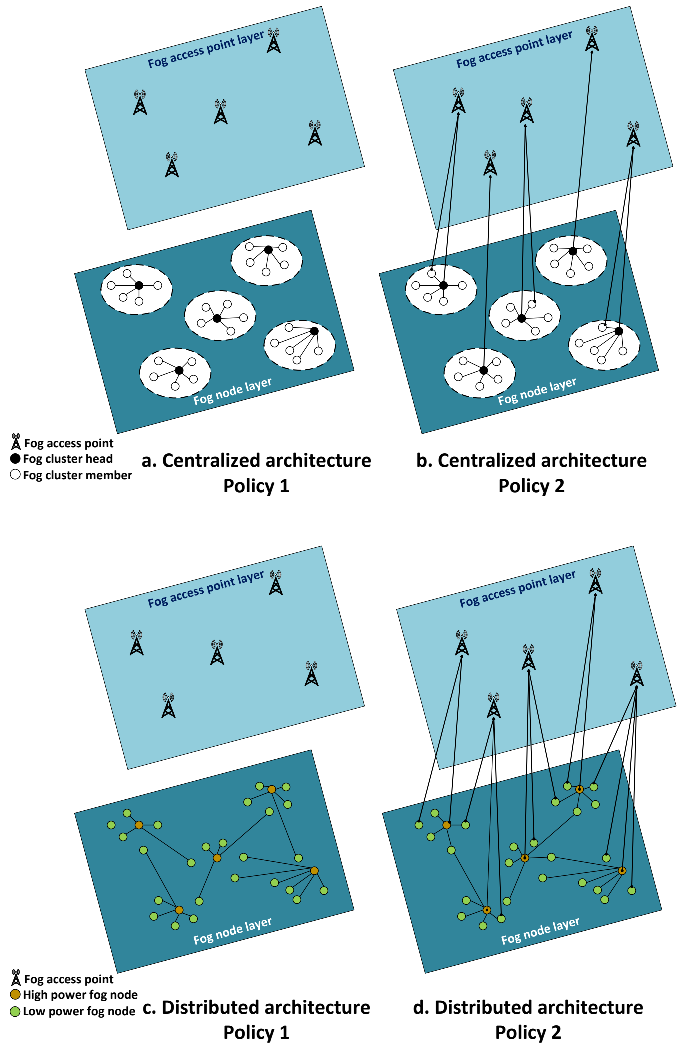

Fig. 5: Centralized and distributed architecture

b) Distributed architecture.

In this architecture, no clusters are formed and fog nodes from the LPFN group can select any available fog node from the HPFN group and from F-APs within their coverage area. Two policies are used:

(i) Policy 1. In this policy, only fog node layer is used for task offloading and LPFNs can partially offload their tasks to HPFNs within their coverage area.
(ii) Policy 2. In this policy, both the fog node and F-APs layers are used for task offloading. LPFNs can partially offload their tasks to both HPFNs and F-APs.

Numerical results obtained in [123] show that (a) When only the fog node layer is considered for task offloading, then in the centralized architecture, the delay increases when the number of fog nodes increases. In contrast, in the distributed architecture, the delay decreases when the number of fog nodes increases as more options are available for task offloading. (b) When both the fog node layer and the F-AP layer are considered for task offloading, then in the centralized architecture, the delay decreases when the number of fog nodes increases as more tasks are offloaded to the F-AP. However, in the distributed architecture, the delay increases when the number of fog nodes increases.

3) Fog node location and resource planning: Silva et al. [106] solves the fog node location and resource planning problem to improve QoS and energy efficiency of the network. QoS is improved by reducing the outage time of time sensitive applications caused by the non-availability of resources at the fog node, and network energy efficiency is improved by processing the maximum number of tasks and applications in the fog node. The work evaluates the achieved gain to place fog nodes at different locations. The gain is a function of the proportion of fog-only applications accepted and the amount of energy saved because of this placement. An acyclic directed graph, where the edges are assigned weight in proportion to the gain achieved if that vertex is selected as the fog node, is used to find the optimal fog node location. Optimal computation, power and storage resources required in a fog node and location of the fog node are evaluated so that the maximum number of users can be served.

Wu et al. [124] employs forward deployment of computing servers to achieve optimized latency and load balance in the network. When computing servers are in close proximity of the fog nodes, the transmission latency and transmission power required to offload task from fog node to computing servers greatly reduces. This encourages fog nodes to offload maximum tasks to these forward computing servers to conserve their energy and computation resources, thus achieving energy efficiency.

C. Energy aware device control

Task offloading conserves energy. However, the amount of energy saved can be further improved if task offloading is used in conjunction with device control based energy conservation techniques. These techniques control some functions or features of devices to regulate them for better performance and energy conservation. With device control, local devices and task helper nodes can control parameters such as transmission power, on/off switching time, battery supply voltage, battery supply frequency, and modulation scheme.

1) Transmission power optimization: Task offloading saves local computation energy at the cost of higher transmission energy to offload portion of the task to the task helper node. Transmission energy depends on factors such as the distance between the local and task helper devices, atmospheric conditions, path losses, interference and collision. These factors can be managed through various techniques to save/optimize transmission energy. We describe some of these approaches that have been used in the latest research below and Table V presents a summary of these recent works.

Yang et al. [126] used an adaptive modulation scheme to optimize transmission energy. The modulation scheme and the size of data offloaded are adjusted according to the channel conditions to reduce transmission losses. They also proposed a method to improve spectral efficiency by using unused spectrum of busy nodes. To achieve this, the task node senses for unused spectrum and then cognitively accesses it by adapting its spectrum parameters.

Abkenar et al. [127] seeks the optimal transmission power and transmission rate based on channel conditions and the outage probability of fog nodes. Selected power and transmission rate ensure that at least one fog node successfully receives the request so that additional energy is not be wasted during a re-transmission.

Fu et al. [128] proposed energy harvesting of edge devices from the base station according to the workload generated at the edge devices. The proposed scheme provides sufficient energy to the edge devices that enables them to compute most of the generated tasks locally. This significantly reduces the amount of uplink transmitted information from the edge devices to the base station, thus minimizing the transmission energy used.

2) Switching on/off of devices: When the devices are not in continuous use and are needed for some specific operations only, then, these devices can be switched off completely or partly to save energy. Some of the methodologies include [132]: (a) Duty cycle control in which on and off time of the device transmitter is adjusted, (b) Passive wake up in which on and off mechanism of the device is triggered by an external event or signal (wake-up signal), (c) Topology control protocols which exploit network redundancy to dynamically adapt the network topology by reducing the number of active nodes based on the application's needs. These techniques require a good regulatory procedure to ensure their availability when needed. Since fog nodes play a pivotal role in the IoT network and all devices are connected everywhere through them, they can be used to control such functions.

Venanzi et al. [129] proposed to control the on/off mechanism of the device's Bluetooth Low Energy (BLE) [133] interface using fog nodes. The BLE interface is used by the devices to connect and communicate with each other as: (1) BLE-advertiser, that wants some service/ information for which they advertise their information to be discovered and, (2) BLE-scanner, that scans for BLE-advertisers to serve. The continuous BLE advertisement and BLE scanning could result in high energy consumption of the devices. In the proposed scheme, the fog node turns off the BLE interfaces of devices until a BLE-advertiser reaches the discover-able range of a BLE-scanner. The fog node has geo-location capability through which it keeps track of the device's location and movement.

In their work, the authors consider slow moving devices (pedestrian) that are also connected with the fog node over the Wi-Fi link. To improve energy efficiency of the devices, the Wi-Fi link of the devices is turned off according to a timer. The fog node estimates the optimal wake-up time of the device's Wi-Fi link using the speed and direction of the devices. However, in a high density scenario where devices move continuously, this mobility can create a situation where BLE interfaces are kept 'on' continuously. Under such circumstances, the proposed scheme will fail because extra energy will be spent on maintaining the Wi-Fi link with the

TABLE V: Research work - Energy aware device control

Yr	Reference	Transmission optimization	Device on/off	DVFS	DVS	DMS	Key idea	Energy efficiency target	Performance metric
2018	Yang et al. [126]	Y	-	-	-	-	Uses adaptive modulation scheme Improves spectral efficiency through spectrum sharing	Transmission power	Energy consumed Spectrum bandwidth and access probability effect on energy consumed
2019	Abkenar et al. [127]	Y				-	Finds optimal transmission power and transmission rate based on channel conditions and outage probability of fog nodes	Transmission power	Energy consumed Average delay Energy balance (fairness) among fog nodes
2020	Fu et al. [128]	Y	-	-	-	-	Reduces requirement for uplink transmission by providing energy through energy harvesting	Uplink transmission power Mobile edge devices	Energy consumed Uplink transmission power
2019	Venanzi1 et al. [129]	Y	Y	-	-	-	Optimizes transmission power by using fog node to switch on/off: Device BLE interfaces WiFi link of BLE devices	BLE devices	Energy consumed
2020	Hou et al. [113]	-	-	Y	-	-	Applies DVFS on cloud servers to dynamically adjust their power consumption according to workload and manage number of active servers	Data center	Average energy efficiency Average queue length
2020	Chen et al. [130]	Y	-	-	Y	-	Applies DVS on fog nodes to optimize transmission power and local Central Processing Unit (CPU) computation speed	Fog node	Energy consumed Task completion time Algorithm convergence time
2020	Karimiafshar et al. [131]	Y			Y	Y	Applies DVS to control fog node's CPU energy consumption Applies DMS to optimize fog node's transmission power	Fog node	Service time Number of deadline misses

Bluetooth Low Energy (BLE), Dynamic Modulation Scaling (DMS), Dynamic Voltage and Frequency Scaling (DVFS), Dynamic Voltage Scaling (DVS)

devices.

3) Dynamic Voltage and Frequency Scaling (DVFS): DVFS is a combination of hardware and software technologies to achieve energy efficiency. The DVFS scheme is widely used in most modern architectures to minimize power consumption by dynamically adjusting the frequency and supply voltage to various processors, controller chips and particular components according to the workload. Since frequency and voltage directly affect the energy consumed, therefore, scaling them up with increase in workload will result in more energy consumption and, scaling them down with decrease in workload will result in decrease in energy consumption. Scaling the frequency and supply voltage up or down according to the workload, results in optimal resource utilization and energy conservation. The DVFS scheme is used in almost all modern computer hardware to maximize power savings, battery life and increase the longevity of the devices while still maintaining computing availability.

S. Hou et al. [113] uses DVFS scheme on cloud servers to enable them to dynamically adjust their voltage supply and operating frequency. With DVFS, servers dynamically adjust their voltage and operating frequency and control the number of active servers for each data center as well thereby reducing the overall energy consumption.

4) Dynamic Voltage Scaling (DVS): Unlike the DVFS scheme, DVS only uses dynamic voltage to control the energy consumption of the device. Chen et al. [130] makes task offloading decision at the fog node using Lagrangian dual theory and then uses the DVS scheme to further improve energy efficiency by jointly optimizing offloading ratio, transmission power, local Central Processing Unit (CPU) computation speed and transmission time.

5) Dynamic Modulation Scaling (DMS): DMS dynamically scales the modulation level to optimize the transmission speed to save transmission energy. The transmission speed is optimized by adjusting the number of bits that get transmitted according to the number of packets that need to be transmitted at that particular time interval. In general, the DMS technique finds a trade-off between transmission energy and transmission delay. Karimiafshar et al. [131] have used DVFS along with DMS. The authors assumed that the fog nodes are equipped with DVFS capable CPUs and DMS capable radio peripherals. DVFS optimizes the CPU energy consumption by dynamically adjusting the CPU's frequency and voltage, whereas DMS optimizes the transmission energy consumption.

D. Energy aware Energy Harvesting (EH)

IoT devices are now designed as small and wireless portable electronic devices which are often powered by an on-device

TABLE VI: Research works on EH based on RF transmissions and efficient utilization of green energy from renewable energy sources

Year	Reference	Key idea	SWIPT architecture	EH source	EH target devices
2019	Zheng et al. [134]	EH over TDMA using fog assisted HAP	Power splitting	HAP	Sensors
2020	Liu et al. [135]	EH over OFDMA using fog assisted HAP Employs fairness in EH by harvesting more energy for low power IoT devices than high power devices	Time switching	HAP	End devices
2020	Fu et al. [128]	EH from mobile edge computing assisted base station using full duplex SWIPT system and MIMO antennas	Power splitting	Base station	End devices
2020	Cai et al. [136]	Task fog node jointly offloads task and energy to the helper fog nodes using SWIPT over TDMA	Time switching	Task fog node	Helper fog node
2020	Tang et al. [137]	EH of IoT devices in which batteries are charged using green energy from renewable energy sources such as solar and wind, etc	Not supported	Renewable energy sources (solar and wind)	IoT devices
2020	Karimiafshar et al. [131]	EH of fog nodes using green energy. No batteries are used at fog site Fairness is achieved in green energy consumption by making task offloading decisions based on available renewable energy and current workload	Not supported	Renewable energy sources (solar and wind)	Fog nodes

Energy Harvesting (EH), Hybrid Access Point (HAP), Internet of Things (IoT), Multiple-Input Multiple-Output (MIMO), Orthogonal Frequency Division Multiple Access (OFDMA), Simultaneous Wireless Information and Power Transfer (SWIPT), Time Division Multiple Access (TDMA)

power supply using various types and sizes of batteries depending on the application requirements. These batteries can store a finite amount of energy only, and therefore they need to be recharged or replaced periodically, which becomes a big issue in cases such as (a) large scale IoT deployments (b) sensors placed inside the human body (c) and devices placed inside the wall or in a toxic environment. Depletion of battery power results in the non-availability of the devices which can be detrimental to the network. This requires the development of alternate means of charging of devices especially sensors, which is now recognized as one of the grand challenges of the IoT revolution [138].

To overcome this problem, EH has emerged as an efficient solution which can offer a viable alternative to autonomously power IoT devices [101]. EH is a process by which IoT devices can increase their energy level by using any ambient sources such as solar, wind, vibration or Radio Frequency (RF). EH helps to extend the life cycle of devices for attaining self-sustainability. We focus on RF based EH techniques in this section.

1) Simultaneous Wireless Information and Power Transfer (SWIPT): The concept of Wireless Energy Transfer (WET) was first introduced by Tesla in 1891 but was considered hazardous due to usage of high power transfer [95]. With the advent of low power transfer (which is not hazardous) and improvement of low power devices, the concept of WET has gained importance and SWIPT is one of the latest research trends in wireless communications where both information and energy are carried by the same wireless signal. A SWIPT receiver randomly switches the communication mode to harvest information or energy or both of them. SWIPT can ensure a stable energy supply in all kinds of weathers, and therefore ensures a longer lifespan of devices in energy constrained systems.

2) SWIPT architecture: There are four SWIPT architectures:

Time Switching (TS): The same antenna is used by the receiver for information transfer and EH. Signal splitting is performed in the time domain and the entire signal received in one time slot is used either for information decoding or power transfer. The TS architecture is simple to implement and requires a switch before the receiver that switches incoming signal between charging circuit and signal receiver but requires accurate time synchronization and information/energy scheduling.

Power Splitting (PS): PS is used to achieve information and power transfer simultaneously. It is achieved by splitting the received signal into two streams of different power levels, one for the information transfer and other for EH. Since the signal received in one time slot is simultaneously used for both information decoding and power transfer, therefore, it is more suitable for applications with critical information/ energy or delay constraints requirements.

Integrated ID/EH receiver: This architecture uses a rectifier to convert RF-to-baseband to generate a DC current. Then, the DC current is divided by a power splitter into two power streams. One is used for EH and another one for information transfer.

Antenna Separated (AS): Separate antennas are used for information transfer and EH through which simultaneous information transfer and EH can take place. Separate frequencies can be used for information transfer and EH. This system is also known as separate receiver architecture.

When the power consumption of the circuit is low and more EH is expected, the integrated ID/EH SWIPT architecture outperforms PS, TS, and AS receiver architectures. But when the power consumption of the circuit is high, PS, TS, and AS performs better. It has also been found that PS performs better than TS in terms of throughput at high SNR and TS performs better than PS at low SNR [95].

Table VI presents a comparison of different EH techniques used in recent research works for fog enabled IoT networks.

Zheng et al. [134] used Hybrid Access Point (HAP) controlled by the fog node to harvest energy in the sensor nodes using Time Division Multiple Access (TDMA) and PS SWIPT architecture. HAP provides harvesting energy to the sensor nodes according to their workload. This harvesting energy is sufficient for the sensor nodes to perform the generated task locally or offload that task to the fog node for processing.

Liu et al. [135], used HAP to harvest energy in the end devices over Orthogonal Frequency Division Multiple Access (OFDMA) using TS SWIPT architecture. The energy harvesting is done considering two factors: (1) The amount of work generated at the end devices and, (2) The remaining energy of the end devices. The proposed scheme ensures fairness in terms of remaining energy of the devices. This is achieved by providing more harvesting energy to the end devices with low remaining energy and vice versa.

Fu et al. [128] used base station to harvest energy in the end devices according to their workload. The base station used full duplex SWIPT system employing Multiple Input Multiple Output (MIMO) antennas. The end devices used PS SWIPT architecture for EH. This harvested energy is used by the end devices to perform generated tasks locally or offload them to the base station for processing.

Cai et al. [136] considers the scenario wherein the task node has sufficient power source and helper nodes have low power resources. In this case the task node offloads both task and energy to the helper node. The purpose of task offloading is not save energy but rather to save computation resources.

Tang et al. [137] proposed the use of green energy sources (solar and wind) with IoT devices to save their energy. In contrast, Karimiafshar et al. [131] uses green energy sources with fog nodes only. To reduce carbon emissions, the work assumes that fog nodes have no batteries and operate on green energy or electric power. Green energy production and consumption is different at different fog nodes. Therefore, the authors developed algorithms to perform task offloading decisions based on available green energy and the current workload of the fog nodes.

IV. QoS AWARE TECHNIQUES FOR ENERGY EFFICIENT FOG COMPUTING IN IoT

Improving energy efficiency in the network has many benefits such as reduced network operational cost, enhanced network life and availability of computation critical devices. However, there are many other techniques that focus on other QoS features in addition to the energy efficiency. We classify energy efficient techniques to improve QoS into seven categories namely, latency reduction, fair offloading, fog node cooperation, load balancing, fault tolerance, accuracy and privacy assurance, and resource allocation as Fig. 6 shows. Tables VII, VIII and IX summarize the recent works related to these seven categories.

A. Latency reduction

Computation tasks are limited by the maximum latency, which serves as the main constraint while making task of-

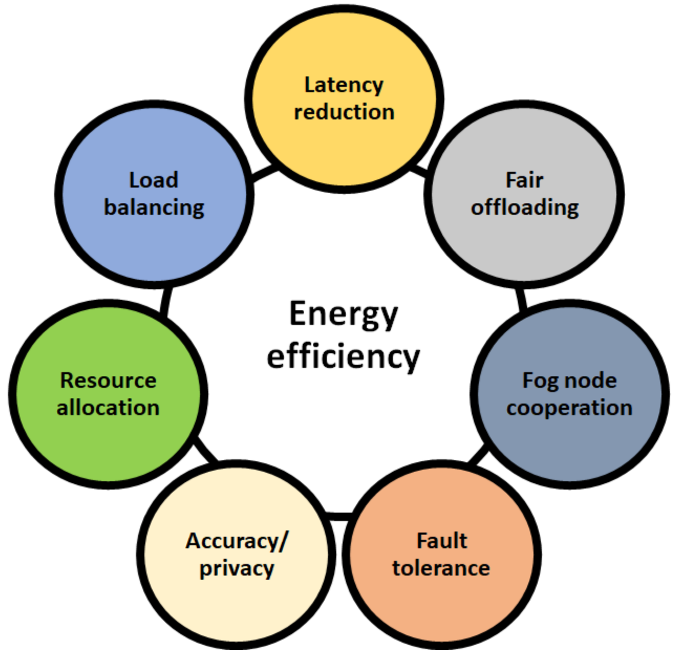

Fig. 6: QoS aware techniques for energy efficient fog computing in IoT

floading decisions. Failure to meet the latency requirements result in data lag and application failure. On the contrary, if latency is improved and the task is executed in a shorter period of time, it greatly improves the user experience of an application/ service, which is vital for applications' survival in a competitive environment.

Kim et al. [112] adopts the methodology to always process frequently requested tasks in the fog node. Since frequently requested tasks are always large in number, therefore, many tasks get processed in the fog node, which results in an overall improvement in service time/ latency of frequently requested tasks.

Jiang et al. [104] has proposed an algorithm that selects the offloading device using criteria such as minimum workload (i.e., short task queues) and maximum remaining energy. When a task is offloaded to a device with a short task queue, the wait time, for executing of offloaded task will also be short. This reduces the total time for task execution and also ensures load balancing on the network.

B. Fair offloading

Fog IoT network consists of many heterogeneous devices with varying computational, storage and power resources, owned by various owners. Fair offloading among devices while maintaining a satisfactory energy efficiency is of great significance, not only for the sustainability of the network but also for enabling the fog node owners to continue resource sharing. Fairness, however, comes at the cost of increased delay. Thus, a trade-off is needed between fairness and delay to ensure task completion within given time constraints.

Abkenar et al. [127] achieves fairness and does energy balancing among fog nodes by using fog node's remaining energy as weight in determining the utility function, used in

TABLE VII: QoS aware techniques for energy efficient fog computing

Reference	Latency reduction	Fair offloading	Load balancing	Fog node cooperation	Fault tolerance	Accuracy/privacy	Key idea
Kim et al. [112]	Y	-	-	-	-	-	Tasks with high occurrence probability (popularity) are processed at the fog node to improve energy efficiency and latency
Jiang et al. [104]	Y	-	Y	-	-	-	Chooses offload device that has:- Minimal workload Maximum remaining energy
Abkenar et al. [127]	Y	Y	-	-	-	-	Uses fog node's remaining energy as weight in determining the utility function
Zhang et al. [111]	-	Y	-	-	-	-	Makes task offloading decisions based on fog node's power source and remaining energy
Liu et al. [135]	-	Y		-	-	-	Achieves fairness in remaining energy of the end devices by providing harvesting energy to the end devices according to their workload and remaining energy. The end devices with low remaining energy are provided more harvesting energy and vice versa to balance the overall remaining energy of the end devices
Dong et al. [139]	Y	Y	-	Y	-	-	Proposes fairness cooperation policy based on a system of rewards and punishments. The more resources a fog node contributes, the more help it will receive when it has a high workload
Huang et al. [109]	-	-	Y	Y	-	-	Finds fog node's willingness to compute offloaded tasks of other fog nodes and perform load balancing based on queue length, historical energy consumption and current status
Li et al. [140]	Y	-	Y	-	Y	-	Balances load among network layers to achieve energy efficiency Unfinished tasks due to any fog node failure are offloaded to other devices
Saraswat et al. [141]	Y	-	-	-	-	Y	Handles ubiquitous system application tasks that are very sensitive to data accuracy and deadlines. The processed information may lose importance if delayed
Chen et al. [142]	-	-	-	-	-	Y	Data is encrypted before offloading from one layer to the next. Public and private keys are used for security.

'Y': supported
'-': not supported

making the task offloading decision. The fog node with the least residual energy will be given less tasks and the one with more residual energy will be assigned more tasks. To cater for the time constraints, trade-off is done between fog node's remaining energy and delay to select the best fog node that has the lowest processing delay and maximum remaining energy.

Zhang et al. [111] achieves fairness by considering the power source of the devices. Battery powered devices are given less tasks to ensure their long stay in the network, while work is fairly distributed among electric powered devices. Fairness is achieved through a scheduling metric (weight/ value used in selection of a fog node), which will be high for a: (a) fog node which provides lower overall task offloading energy consumption, (b) fog node that has high a scheduling priority (i.e., fog node that has electric power supply), (c) and fog node that maintains a lower historical average energy consumption.

Liu et al. [135] uses energy harvesting to provide end devices with the required power resource to perform local computing or offload task to the fog node. The work performs max-min energy balancing by providing harvesting energy to the end devices according to their workload and remaining energy. The end devices with low remaining energy are provided more harvesting energy and those with high remaining energy are provided with less harvesting energy to balance the overall remaining energy of the end devices Using this approach, the authors achieve fairness in the remaining energy of the end devices.

C. Fog node cooperation

It is widely accepted that fog nodes will process offloaded tasks with all of their computation capabilities, and all fog nodes would be willing to accept offloaded tasks from their neighboring devices. However, a portion of fog nodes may not be willing to share their resources and may want to apply different resource allocation policies to control their computation, storage, and power resources. Some of the reasons for this control may include: money, energy conservation, and avoidance of traffic congestions/ long queues. For this reason, some researchers have incorporated algorithms in their works to seek the fog node's willingness to participate before making resource allocation decisions.

Dong et al. [139] has proposed a fairness cooperation policy that incorporates both fairness in task distribution and the fog node's willingness to cooperate. Fog node owners decide the amount of their resources to share in each task offloading assignment. The focus of the work is to create a healthy cooperation environment among fog nodes, in which fog node owners feel comfortable and are encouraged to cooperate and commit their maximum resources by: (a) ensuring fairness in task distribution, (b) employing a policy of reward and punishment against the percentage of their resources shared. The more resources a fog node contributes, the more help that fog node receives from other fog nodes when it has a high workload.

D. Load balancing

is an important QoS feature which ensures that no device is overworked and it also stabilizes network operations. Load balancing generally reduces task queues in the devices which decreases tasks' completion times.

Huang et al. [109] has incorporated both a fog node's willingness to cooperate and load balancing in their proposed work. To receive a fog node's willingness to participate, devices broadcast their task information against which, willing fog nodes calculate report based on historical average energy consumption and the current task offloading energy consumption. From this report, the fog node decides to offer complete, some, or no resources to the device. Load balancing is achieved by making a trade-off between the historical average energy consumption status of the fog node and the queue length at that fog node. A fog node with a high historical status will be considered last for task allocation. However, if it has smaller queue lengths, then it may be considered with a higher probability.

E. Fault tolerance

is ability to provide the desired service despite the presence of certain failures in the system. Li et al. [140] have used both load balancing and fault tolerance in energy efficient task offloading. A task can be offloaded to three layers, namely, edge, fog, and cloud. Load balancing is achieved by determining the minimum/optimum workload for the edge and fog layers beyond which tasks are offloaded to the next higher layer (fog layer for the edge devices and the cloud layer for the fog devices). However, if the task arrival rate at a layer is less than the service time, then task will be processed in the same layer.

Fault tolerance is incorporated in fog nodes to ensure the completion of all tasks offloaded to the fog nodes. The offloaded tasks are traced and if one fog node leaves the system when it runs out of power and has an unfinished task, then that task will be offloaded to another fog node for execution.

F. Accuracy and privacy assurance

Some researchers have also incorporated data accuracy and privacy while achieving energy efficiency. Saraswat et al. [141] proposed a Ubicom system which consists of tiny, battery powered devices called leaf devices that contain sensing units for monitoring the environmental activities at periodic intervals of time. These applications are very sensitive to data accuracy and deadlines, as their information may lose importance if delayed such as Amazon echo speaker and Apple watch. The authors used queuing theory to distribute workload among edge, fog, and cloud layers to ensure task completion within deadlines while ensuring data accuracy.

Wang et al. [108] proposed a trust model for fog nodes to evaluate the information generated by sensor nodes. The sensor nodes may collect invalid or misleading data due to noise and malicious attacks which cause faster energy consumption through an increase in transmission activities, thereby, reducing the life of the sensor node. Two methods are used by fog nodes to determine their trust on sensor nodes:
a) Direct evaluation method. For each direct neighbor, direct trust is calculated from: (1) Historical communication interactions, (2) Node residual energy and (3) Node packet loss rate.
b) Indirect evaluation method. For all nodes that are not directly connected with fog node, indirect trust is calculated based on the direct trust value of its direct neighbor. Nodes are divided into clusters and cluster heads are selected based on the trust value.

Chen et al. [142] proposed a privacy and energy aware data aggregation computation offloading scheme for fog assisted IoT networks. The data communication between layers is encrypted to protect against eavesdropping and compromising attacks. A trusted authority is used to generate public and private keys which are used by sensing layer and cloud layer. After their computations, both the sensing layer and the fog layer send their results to the cloud layer which uses its private key to decrypt the received information and aggregate the results obtained.

G. Resource allocation

Fog computing has no dedicated resources and relies on computation resources of available devices (such as smartphones) in the network. The versatility of resources opens up the challenge of availability and efficiency while developing resource allocation and scheduling schemes in fog IoT networks. Furthermore, each fog device is primarily responsible for its own computation tasks and performs other computation activities after. If the fog device is fully utilized in own tasks, then it will not do any processing for other devices. These limitations make resource allocation and task scheduling a key challenge in running IoT applications in a fog computing environment [143].

For efficient resource allocation, resource schedulers have to consider all available computing devices/ nodes, know their resources and information about their ongoing computation tasks. They have to balance various computations, communication and latency constraints to distribute the workload to achieve energy efficiency while not overloading the computing devices to deplete them of their resources. The process of resource allocation in fog computing based IoT networks is facilitated through: accurate network information and learning algorithms.

1) Methods for obtaining network information: Having accurate information about the network is a key requirement for the devices to make efficient resource allocation decisions. Edge devices lack network information and frequently offload to the nearest fog node only. However, fog nodes act as the main resource manager and decision maker in the fog IoT network, for which it is either provided with the network information by some central controller (*centralized method of obtaining network information*) or it learns the information from its environment using various techniques (*distributed method of obtaining network information*). Table VIII presents some of the techniques used for collecting network information for resource allocations.

TABLE VIII: Methods for obtaining network information

Network information	Reference	Network information learning process
Centralized	Yang et al. [126]	Centralized controller makes offloading decision for which it obtains network information from base station
	Gai et al. [114]	Task offloading tables are pre-stored in fog servers based on which the initial sub-optimal task allocation plan is prepared
	Fu et al. [128]	Mobile Edge Computing (MEC) server is placed inside the base station and it obtains all information from there
	Zhang et al. [111]	A virtual container that has complete information of network resources is considered. It makes offloading decisions
	Li et al. [140]	Assumes that the monitoring center responsible for scheduling tasks is in the cloud
	Abkenar et al. [127]	Assumes that task fog node knows location of the helping fog nodes
	Karimiafshar et al. [131]	Central controller makes all offloading decisions
Distributed	Zu et al. [110]	Task fog node broadcasts task's information against which the helper fog node proposes task node with the best channel
	Huang et al. [109]	End device broadcasts task information which is used by the fog node that is willing to participate in task offloading process

2) Learning algorithms for obtaining network information: Machine learning based algorithms are used for efficient resource allocation in fog IoT networks. Table IX presents a summary of recent works in this area and we provide the details below.

Zhu et al. [144] uses the Deep Learning (DL) technique to solve energy and delay constraints for fog node to fog node offloading. The work jointly optimizes offloading ratio (ratio of offloaded tasks to computation tasks processed for other fog nodes), local Central Processing Unit (CPU) resource utilization, bandwidth used and external CPU resource utilization while meeting the constraints. A Deep Neural Network (DNN) is trained on the labeled data to output the optimal offloading action. Every layer in the constructed DNN is fully linked and the gradient descent algorithm is used to minimize the cross entropy loss for gaining the optimal parameter values.

While doing resource allocation, researchers assume that IoT devices have complete state information about the system whereas in practical situations, it may not be the case and IoT devices may only have partial information about the system. Tang et al. [137] explored the decentralized partially observable offloading problem wherein energy harvesting enabled IoT fog systems make offloading decisions based on their local observations of the system. The authors formulated the optimization problem as a decentralized partially observable Markov Decision Process (MDP) and developed a learning-based decentralized offloading algorithm to solve the problem. The objective of the proposed MDP formulation is to maximize the reward of the system which is reduced electricity cost while taking into account the current number of its remaining tasks, the renewable battery energy level, and the availability of the fog node's resources.

The authors applied the Lagrangian multiplier function and the policy gradient method to find the local optimal solution for the problem. At the beginning of each time slot, the fog node transmits its task queue state to all IoT devices. The IoT devices make offloading decisions on the basis of queue state information of fog node and local observation of its system state (i.e., remaining tasks and renewable battery level). A portion of the tasks are processed locally by the IoT devices, whereas, others are offloaded to fog node for processing.

Mebrek et al. [145] proposed a reinforcement learning based algorithm that allows users to learn the optimal policy for service request distribution over the fog-cloud system without a priori knowledge of the dynamic statistics of the system. The optimization problem is formulated as a Nash Equilibrium problem, which allows the trade-off between the energy consumed by the system and the QoS. The user chooses a fog node (from many fog nodes) or cloud while monitoring the current state of its environment. The user keeps estimates of the effect of its decision on the reward, and the combined actions of all the agents that produced a transition to a new state. These estimates constitute the Q-function, and are used by users to make resource allocation decision. By observing the actual incurred costs, the users update these estimates over time, and by doing so, also improves its policy for service request distribution over the fog-cloud system.

Sen et al. [146] formulated a deadline aware, energy efficient task offloading problem to schedule tasks between the three tiers, i.e., cloud, fog, and edge devices. The cloud server gathers information regarding the incoming task and node resource characteristics from all the edge nodes. Afterwards, it performs reinforcement learning training by deriving the state which corresponds to the task and node resource characteristics, and calculates the reward associated with the actions. The cloud server makes a Q-value table which is distributed to each node. Nodes use this lookup table to decide where to run the task, i.e., by itself, at the fog or the cloud. The edge nodes report the task assignment activities to the cloud server which keeps updating the Q-value table. This lookup operation reduces the complexity of the task assignment problem and reduces the solution time to near real-time.

Yang et al. [147] considered an industrial network architecture which uses heterogeneous Radio Frequency (RF) and Visible Light Communication (VLC) to meet different QoS requirements of devices. Devices were divided into two groups. Group 1 contains devices with low latency and high reliability requirements but do not have high data rate requirements. These devices are served by the RF access point. Group 2 contains devices that have high data rate requirements but are less

TABLE IX: Resource allocation in fog IoT networks - Learning based techniques

Year	Reference	Problem	Learning technique	States	Actions	Rewards
2019	Zhu et al. [144]	Energy and delay aware resource allocation in fog computing	Deep learning with gradient descent	-	-	Energy and time optimization
2020	Tang et al. [137]	Energy harvesting enabled IoT devices do not have complete system information and have to make offloading decisions based on partial global observation of the system	Decentralized Markov decision process with policy gradient algorithm	Data queue Renewable energy queue	How much of the task to offload to the fog node	Reduced electricity cost
2019	Mebrek et al. [145]	Distributed resource allocation decision by users without having prior knowledge of the system dynamics	Q-learning based reinforcement learning scheme with ascendant gradient	Average request arrival rate Transmission rate Task size Request size distribution	Choose a fog node from a set of fog nodes 'OR' choose cloud	Energy efficient resource allocation
2019	Sen et al. [146]	Energy efficient task scheduling among the three tiers i.e., cloud, fog and edge devices	Q-learning based reinforcement learning scheme	CPU capacity Available bandwidth	Edge node assigns a task to itself, fog within its region or the cloud	Energy and time optimization
2020	Yang et al. [147]	Choose from heterogeneous radio frequency/ visible light communication networks and select energy efficient access point to meet QoS requirements of devices	Markov decision process Post decision state based experience replay and transfer reinforcement learning algorithm	Sub-channel usage status Channel quality Service application types Service satisfaction	Communication network selection Sub channel assignment Transmit power management	Maximize network energy efficiency while satisfying the minimum data rate constraints

'-': Not supported

interested in the latency and reliability requirements. These devices are served by the VLC access point. Devices shift from one group to the other with changes in the application service's requirements. The selection of the network and an access point with the least energy consumption is formulated as a MDP and a new deep Post Decision State (PDS) based Experience Replay and Transfer (ERT) reinforcement learning algorithm is proposed to achieve intelligent resource management. Instead of directly using the selected native action strategy to update the Q-function, PDS-ERT calculates the similarity level between the current agent and other agents (historical policy) to generate an overall action. The experience learned with the best reward is recorded in the relay memory for future use.

V. Future opportunities and open challenges

There are several challenges that must to be addressed while designing, modeling, and implementing fog-based energy-aware 6G-enabled massive IoT architectures, policies, and applications. We discuss some research opportunities and challenges that need further attention for enabling 6G-based energy-efficient solutions for massive IoT-fog environment.

A. Resource management

Resource management in a distributed system refers to the management of computing and storage resources. It is a challenging task to find out the available suitable fog nodes in the vicinity of the IoT devices. In an IoT-enabled fog network, resource allocation and task offloading play a central role in energy-aware resource management. It is important to utilize fog resources efficiently to avoid the wastage of energy. In such networks, the utilization of resources is not identical and there are frequent variations in the pattern of IoT traffic. Hence, it is considered to be a highly dynamic environment that makes resource management even more challenging. Consequently, it requires sophisticated and smart approaches that achieve a trade-off between the optimization of resource utilization, energy consumption, and quality of service requirements of the application and services. In this context, load-balancing techniques can also be effective to avoid the unnecessary delays, optimize the bandwidth, and improve the utilization of resources. However, these techniques should also ensure the energy-efficiency of the network. For instance, at lower network load (of IoT jobs) conditions, load-balancing techniques are not as effective because the jobs can be easily processed by the nearby fog devices, and redirecting the jobs to other fog devices can increase the communication and management overheads. Additionally, it can be ineffective to utilize and balance the load among all available fog devices when the jobs can be handled by a few fog devices. To achieve this, we need a scalable and cost-effective resource management and load-balancing strategy to efficiently manage the fog resources.

B. Heterogeneity

Heterogeneity refers to the differences in software and hardware. This concept is also applied for the various types of jobs that need to be processed by fog nodes. In an IoT-enabled fog network, there are various types of IoT and fog devices having different hardware and software. Moreover, there are multiple IoT applications that execute in the IoT-enabled fog network. These applications have different storage and computing requirements. In such a highly heterogeneous environment, it is challenging to apply energy-aware mechanisms. Moreover, heterogeneous operating systems have different power consumptions which can be optimized to consume less power. This issue cannot be neglected because different versions of the same operating systems may also exhibit variations in the power that they consume. An operating system can manage its operations to deal with energy issues. In the case of fog devices with different hardware and software specifications, the execution time and synchronization issues need to be addressed for storing and computing the different types of IoT requests. Hence, the traditional energy-efficient policies are hard to apply because of the heterogeneity of the IoT-enabled fog environment. Similarly, the various generations of wireless technologies (from 1G to 6G) are also expected to be compatible with the considered mechanisms for smooth operations. From this perspective, efficient handover mechanisms are required to assure acceptable QoS. To address the heterogeneity issue in fog computing, semantic-based approaches [148] can be useful. Moreover, developers of IoT applications can also play a major role in addressing the heterogeneity issue by introducing energy-aware procedures as an essential part of the application. There is a need to define policies that consider the energy and thermal constraints while considering the matching criterion of resource capabilities and the requirements of the IoT jobs.

C. Balancing energy-efficiency and QoS-awareness

It is observed that the majority of the energy-aware mechanisms applied in the distributed computing environment have a considerable impact on the QoS. One of the most popular schemes used to save energy in fog networks is the consolidation of devices where the idle or underutilized devices or their components are turned-off or put into sleep mode to minimize energy consumption. This strategy is effective because it allows saving dynamic as well as static energy consumption of the fog-based networks. However, this power-saving scheme can affect QoS in different ways. For instance, when a device is put into sleep mode or turned off, there is a need to redirect the incoming IoT traffic in a timely manner to other available and nearby fog devices. This process can increase the latency because, in an IoT-based fog environment, the IoT requests are sent to the nearby fog node. Hence, serving the request by a fog device that is far from the IoT device (that generated the request) will cause an increase in the delay. Moreover, during the process of turning off a device, there is a slight probability that some IoT requests can be dropped which can significantly affect the performance of the network. Additionally, a smooth and efficient migration of tasks is required from one fog device to another before applying it to the underutilized fog devices. When the traffic of the IoT requests is increased, there is a need to dynamically turn-on the additional fog devices; however, the process of turning-on new devices can take time and can delay serving of IoT requests. Moreover, many electronic devices consume more energy when turned on. Hence, there is a need to find a balance between turning-off and turning-on of the fog devices to avoid unnecessary impact on the QoS. The frequent variations in the state of the fog device may not only affect the QoS but can also degrade the energy-efficiency. Another well-known energy-aware technique is DVFS that deals with the frequency of the processor. Although DVFS can play a role in energy savings; however, it can also affect the performance of the fog-based IoT environment. The processing delay can increase if the frequency of the processor is not well synchronized with the deadline requirements of an IoT job. Hence, we need to develop energy-aware and performance-aware mechanisms to reap energy savings without affecting the service level agreements of application services.

D. Selection of energy-efficient approach

Different approaches are used to improve the utilization of resources and save energy in IoT-enabled 6G fog environment such as energy-aware offloading, energy-aware fog node placement, and energy-aware device control. The selection of an appropriate approach is crucial to achieve maximum energy savings without affecting the performance of the fog network. There are mainly two types of energy consumption in fog computing environment namely, static and dynamic energy consumption. Some approaches target the static energy consumption while others address the dynamic energy consumption. When a device is turned on and it is not processing any job, its energy consumption is termed as static energy consumption. Dynamic energy consumption is the energy consumed while processing IoT requests by a fog device. Static energy consumption is usually higher than the dynamic energy consumption. The selection of an energy-efficiency technique and the decision to target the type of energy consumption in a fog network remains a challenge due to the highly heterogeneous environment and service level agreements of IoT applications. Since dynamic energy consumption is the major component of the total energy consumption of fog nodes, novel techniques that focus on dynamic energy consumption should be further explored.

E. Reconfigurable Intelligent Surface

Reconfigurable Intelligent Surface (RIS) is a key technology used in 6G to improve throughput and reduce latency [14]. A RIS consists of large number of passive elements whose phases can be controlled and reconfigured. By controlling the phase, the reflection characteristics of these surfaces can be altered, thus facilitating the propagation of signal between two wireless nodes.

RIS can significantly improve the throughput of the network and increase the reliability of communications [149]. RIS will also reduce the probability of outage, end-to-end delay and number of transmissions. Thus, tasks from IoT nodes can be efficiently delivered to the fog nodes, requiring lower energy and fewer transmissions. Once the fog nodes have processed the task, they can transmit it back to the IoT nodes with reduced transmission power. Similarly, for data caching applications in the presence of RIS, content can retrieved from the fog nodes with lower energy [150]. A major challenge in RIS assisted fog computing is to efficiently allocate RIS to the multiple IoT nodes. In this context, matching theory based algorithms [151] can be used to find an optimal and stable solution.

F. Federated Learning

To support the large the large amount of data generated from 6G enabled devices, massive computing will be required. Intelligent learning algorithms will be needed to effectively utilize the available computing resources. To reduce the complexity of the learning algorithms for energy-aware task offloading, each fog node can develop a model based on local data such as number of incoming tasks, task sizes, arrival rate of tasks, and energy consumption of the fog node [152].

Fog nodes can share the local learning models with a centralized controller to find a more accurate global learning model. This technique is called federated learning and provides benefits such as security, collaborative data sharing, reduced complexity and more accurate global models. Fog nodes will efficiently save energy in this case by running less complex algorithms and also making more accurate energy-aware task offloading decisions. A key challenge in using federated learning for energy-aware task offloading is to find a global learning model using local models trained on different data sets [153].

G. Energy cooperation

Energy cooperation will be a key component of 6G based fog computing to conserve energy of fog and IoT nodes. Future 6G devices will harvest energy from several sources such as solar, radio frequency etc. Thus, energy cooperation will be needed among IoT and fog nodes to enable massive computation requirements. Nodes with higher available energy can perform tasks on behalf of nodes with lower energy. In addition, intelligent spectrum utilization techniques will also be developed to enable 6G communication and computing [154]. A vital challenge for energy cooperation is to develop incentives mechanisms to motivate fair and honest cooperation among devices [155].

VI. CONCLUSION

This paper provides an overview of massive IoT applications, 6G technology and energy challenges in fog computing. We present a survey of recent works in the area of energy efficient fog computing for IoT networks. We classify recently proposed energy efficient solutions into various categories and summarize their advantages and drawbacks. Finally, we discuss open challenges and highlight future research opportunities for improving energy efficiency of fog computing in 6G enabled massive IoT.

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