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Relaying in the Internet of Things (IoT): A Survey

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ABSTRACT The deployment of relays between Internet of Things (IoT) end devices and gateways can improve link quality. In cellular-based IoT, relays have the potential to reduce base station overload. The energy expended in single-hop long-range communication can be reduced if relays listen to transmissions of end devices and forward these observations to gateways. However, incorporating relays into IoT networks faces some challenges. IoT end devices are designed primarily for uplink communication of small-sized observations toward the network; hence, opportunistically using end devices as relays needs a redesign of both the medium access control (MAC) layer protocol of such end devices and possible addition of new communication interfaces. Additionally, the wake-up time of IoT end devices needs to be synchronized with that of the relays. For cellular-based IoT, the possibility of using infrastructure relays exists, and noncellular IoT networks can leverage the presence of mobile devices for relaying, for example, in remote healthcare. However, the latter presents problems of incentivizing relay participation and managing the mobility of relays. Furthermore, although relays can increase the lifetime of IoT networks, deploying relays implies the need for additional batteries to power them. This can erode the energy efficiency gain that relays offer. Therefore, designing relay-assisted IoT networks that provide acceptable trade-offs is key, and this goes beyond adding an extra transmit RF chain to a relay-enabled IoT end device. There has been increasing research interest in IoT relaying, as demonstrated in the available literature. Works that consider these issues are surveyed in this paper to provide insight into the state of the art, provide design insights for network designers and motivate future research directions.

INDEX TERMS Cooperative communication, energy harvesting, Internet of Things, federated learning, IoT relaying, relay networks, relay selection, secure relaying, SWIPT, UAV, machine learning, artificial intelligence.

I. INTRODUCTION

The Internet of Things (IoT) paradigm allows for the connection of many devices to one another and to the Internet. These devices are usually low-powered sensors deployed to sense the environment and report sensed information through a gateway for information processing and decision making at a central network server using an IP link. Indeed, IoT is being envisioned to be a universal utility [1]. IoT networks are applied in smart agriculture for soil quality monitoring, smart home applications for basic home automation and intelligent road transport. It is envisaged that the IoT will connect billions of devices and will change the way humans and devices

communicate. Cisco [2] projected that by 2023, there will be 14.7 billion M2M connections, which signifies a 2.4-fold increase from the number of M2M connections in 2018.

The IoT is not a standalone concept but builds on existing technologies. The nature of the IoT makes it a candidate for the use of already existing technologies such as machine-type communication, device-to-device (D2D) communication [3] and cognitive radio networks [4]. Moreover, the IoT extends earlier technologies such as radio frequency identification (RFID) and wireless sensor networks (WSNs), solutions that are application-specific with limited interoperability between them [5], [6].

Communication between IoT end devices and a gateway can occur directly or through an intermediary node (a relay). Direct transmission when the distance between an IoT end

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node and the gateway is large can cost the network more power. For practical deployment of the IoT, low-power wireless access network (LPWAN) technologies such as SigFox, LoRa and NB-IoT are designed for at least 1 km of single-hop transmission [7]. Such long-range single-hop communication relies on the quality of a single link and consequently does not enjoy the diversity gain that relayed communication can offer. In [8], it is reported that actual deployments of single-hop IoT networks (using LoRa technology) in rural areas experience connectivity deterioration because a clear line of sight (LOS) between the gateway and end devices is not easily achieved. To ensure reliability, relays can assist in forwarding intended signals from an IoT end device to its gateway. This can be achieved through two or more hops [9]. For short-range IoT connectivity solutions, such as BLE and Wi-Fi-Hola, that use ISM unlicensed bands (which are subject to interference), relays can help extend the transmission range of sensors.

There are differences between relaying in the IoT and relaying in cellular networks. First, most IoT networks are designed for single-hop communication with end devices configured for mostly uplink transmissions of their observations to the gateway. Therefore, using IoT end devices that are enabled to act as relays requires physical interface modifications. Second, IoT end devices are designed to transmit minimal payloads for short durations, and each gateway serves several end devices. Therefore, if end devices are used for relaying, modifications to their duty cycle and messaging windows need to be made while maintaining a lean end device. Such technical constraints make IoT relaying unique. Third, as energy-constrained networks, IoT relays need to balance their energy needs with the energy efficiency constraint of the network. Last, unlike relays in cellular networks that could be part of the network rollout, IoT relays may be remedial measures where the need arises. Consequently, their introduction to the network should be transparent to both gateway and end devices.

IoT relaying poses some questions. For example, should IoT relays be part of network planning or should they be rolled out as an after-thought if the single-hop deployment encounters connectivity deterioration? Moreover, should relays in IoT networks be centrally controlled by either a gateway/network server or should they be transparent relays whose entry and exit from the network go unnoticed by other network components? As research in human-in-the-loop interactions [10] gains traction, implementing user-owned machines (such as drones, cars and smartphones) as relay nodes is also becoming an option. With humans involved, providing incentives to encourage sharing communication resources for IoT data forwarding becomes an issue in addressing and managing the mobility of user-owned machines. Furthermore, it remains to be seen whether relays for IoT networks should be modified end devices or if they should simply be additional gateways [11]. The latter approach incurs some cost, which could dent the low-cost target of IoT networks. Some of these challenges and more have been considered in the literature. This survey reviews the

research conducted in the area of IoT relaying, highlighting the challenges and the approaches adopted to manage them.

A. RELATED SURVEYS

Despite the increasing interest in relay-enabled IoT networks, there is a paucity of surveys in this research area. There are several surveys in the literature that provide overviews and categorization of various aspects of IoT networks; see, e.g., [12]–[24] and the references therein. However, to the best of our knowledge, this survey is the first to focus on the challenges of - and approaches to relaying in IoT networks. We now present a review of selected related survey papers. The selection has been made to have complete coverage of all aspects of the IoT with particular emphasis on their relation to relay-enabled networks.

In [25], the current challenges facing in-band full-duplex relaying are discussed, and open research questions are also highlighted. The authors categorized full-duplex relaying based on relaying strategy, antenna design and spatial streams. It also enumerates relaying schemes designed to overcome the limitations of half-duplex relaying to include successive relaying and two-way relaying, among others. Traditional relaying protocols and clustering techniques are discussed in light of machine-to-machine communication in [26]. Selfish and malicious behavior of nodes are surveyed in [27], where the impact of such behavior on wireless relay networks is presented. Various types of attacks that malicious nodes can launch and the approaches to detect them are also discussed. Incentive mechanisms to encourage data forwarding in such human-centric networks are discussed as well. Different from the work in [25], our survey is not only focused on in-band full-duplex relaying and so has a broader scope. In IoT networks, user-provided machines/devices can serve as relays forming the so-called wireless relay network [27], but relaying in the IoT is not limited to such a scenario; hence, our survey provides a wider scope. Moreover, our survey does not have selfish behavior as its singular focus but also considers such behavior as an aspect of user-provided relaying for which incentive mechanisms can be proposed, as shown in Section IV. The work in [18] limits its focus to relay-assisted wireless body area networks (WBANs). Therein, the authors discuss network architectures, relay node selection and point out the unique quality of service requirements of relay-based WBANs. In Table 1, key related surveys and their focus areas are given to highlight how these surveys differ from our work.

In Table 2, a list of abbreviations used in this article and their meanings are given, and some key features of cellular and IoT relaying are provided in Table 3. Our survey is not limited to a particular IoT connectivity technology because the use of relays has been considered for various connectivity solutions, such as LoRaWAN [29], NB-IoT [30], and Bluetooth low energy [31].

B. KEY CONTRIBUTIONS

As stated above, the focus of this paper is to provide a holistic survey of works that are related to relaying in IoT networks.

TABLE 1. Selected surveys and their focus area.

Article	Type	Area	Technologies	Application	Year Published
[25]	Survey	In-band full duplex relaying	Relaying strategies, antenna patterns and spatial streams	General relaying (non-IoT focus)	2015
[13]	Survey	Buffer-aided relaying	Improved relay selection mechanisms	General relaying (non-IoT focus)	2015
[21]	Survey	Key enabling technologies for IoT	5G, semantic Web, cognitive radio, cloud computing	IoT focus	2017
[26]	Review	Cooperative Communication	Clustering methods and relay selection	M2M communication	2018
[17]	Concepts and overview	Key enabling technologies for IoT	5G IoT enablers (D2D, mmWave, relaying, wireless SDNs, NFVs)	IoT focus	2018 2018
[27]	Survey	Noncooperative relaying	Strategies in overcoming selfish and malicious behaviors in human-centric networks	D2D communication	2018
[16]	Concept and survey	Cooperative communication	NOMA-based D2D communication	D2D communication with focus on industrial IoT	2018
[22]	Survey	IoT architectures	End-to-end architecture descriptions of cyber-physical systems	IoT focus	2019
[14]	Survey	Cooperative communication	Simultaneous wireless information and power transfer with cooperative relay and future challenges	MIMO, WSN, cognitive radio, vehicular ad hoc network, NOMA beamforming techniques and IoT	2019
[23]	Concepts and overview	QoS-aware buffer-aided relaying	Relaying strategies, link selection mechanisms	Wireless Body Area Networks, Healthcare IoT	2019
[20]	Survey	IoT applications	End-to-end taxonomy for IoT applications	IoT applications Smart Cities, Industrial IoT	2020
[28]	Survey	Key enabling technologies for IoT in 5G systems	IoT in 5G enablers (5G NR, HetNets, LPWAN)	IoT in 5G systems	2020
[18]	Survey	Relay node selection and Quality of Service demands	Cooperative diversity, cooperation communication	WBANs	2021
This paper	Survey	Relaying in IoT	Selection algorithms, secure relaying approaches, energy harvesting-based relaying and applications of relaying in IoT	IoT focus	2021

This represents a significant deviation from the few existing survey articles, most of which consider specific aspects of IoT networks and architectures. We believe that researchers, IoT designers and industries will benefit from having a single reference survey covering applications, challenges, advances, solutions and open problems in IoT relay networks. Considering the foregoing, the main contributions of this survey are summarized as follows:

- We provide a taxonomy of the challenges of relaying in the IoT and the research approaches to these challenges as proposed in various studies. To accomplish this, we review current literature in the subject area while also building on more established research contributions in relay networks. Particularly, the approaches are classified as relay selection, secure relay-assisted IoT networks, incentive-based relay-assisted IoT networks, energy harvesting in relay-assisted IoT networks, relay physical interface design and UAV relaying in IoT networks;
- We provide a comprehensive survey of the identified challenges to relaying in the IoT and thoroughly review the literature that has proposed solutions to these challenges;
- We provide a concise review of machine learning (ML) and artificial intelligence (AI) techniques and their

applications in relay-assisted IoT networks. Some insights into other potential issues that can be solved using ML are also provided.

- Considering the interest that UAV relaying in IoT networks is garnering, we thoroughly review aspects of UAV relaying related to IoT networks.
- We highlight key application areas and use cases of relay-assisted IoT networks and provide a survey of highlighted application areas, and
- We discuss open research questions that can provide a road map for future research in the area of relay-assisted IoT networks.

The aim of this article is hence to provide a resource where the merits and demerits of various IoT relaying approaches in the literature are surveyed. We specifically highlight the challenges of relaying in the IoT and the solutions researchers have proposed. We also group the various research works into classes to enable a structured presentation. This will help IoT network designers in their decisions regarding the choice of a design approach. Moreover, researchers can identify future research directions to provide a focus for their work.

The organization of the remainder of this paper is as follows. In Section II, a description of relaying in IoT networks is given with emphasis on classifications of relays and relaying protocols. In addition, a brief background on relaying

TABLE 2. Table of abbreviations.

Abbreviation	Meaning	Abbreviation	Meaning
BSI	Battery State Information	CSI	Channel State Information
SU	Secondary User	AF	Amplify and Forward
DF	Decode and Forward	PHY	Physical layer
MAC	Medium Access Control	HD	Half duplex
IoT	Internet of Things	D2D	Device-to-Device
UAV	Unmanned Aerial Vehicle	NOMA	Nonorthogonal Multiple Access
OFDM	Orthogonal Frequency Division Multiplexing	BER	Bit Error Rate
SNR	Signal-to-Noise Ratio	SWIPT	Simultaneous Wireless Information and Power Transfer
eNB	enhanced Node B	RSSI	Received Signal Strength Indicator
R-D	Relay-Destination	CDI	Channel Distribution Information
VG-AF	Variable Gain Amplify and Forward	OMA	Orthogonal Multiple Access
RS	Relay Selection	S-R-D	Source-Relay-Destination
LTE-A	Long Term Evolution Advanced	LPWAN	Low-Power Wide Area Network
Wi-Fi	Wireless Fidelity	ML	Machine Learning
WBAN	Wireless Body Area Network	SIC	Successive Interference Cancellation
SOP	Secrecy Outage Probability	FD	Full Duplex
CRT	Chinese Remainder Theorem	PLC	Power Line Communication
NB-IoT	Narrow Band Internet of Things	PB	Power Beacon
PS	Power Splitting	TS	Time Switching
R-E	Relay-Eavesdropper	MISO	Multi-Input-Single-Output
MIMO	Multi-Input-Multi-Output	5G	Fifth Generation
FFN	Feed Forward Network	DNN	Deep Neural Network
RNN	Recurrent Neural Network	DT	Decision Tree
SVM	Support Vector Machine	RL	Reinforcement Learning
RS	Relay Selection	AS	Antenna Selection
PHS	Physical Layer Security	CAR	Cache-Aided Relaying
AC	Access Control	PA	Power Allocation
BW	Bandwidth	POS	Position
PTH	Path	FW	Fixed Wing
PWR	Power	AoI	Age of Information
RG	Range	DL	Delay
EE	Energy Efficiency	S/L R	Sum/Link Rate
OP/BER	Outage Probability /Bit Error Rate	CP	Coverage Probability
N_u	Number of Users	RW	Rotary Wing

TABLE 3. IoT relaying and cellular relaying.

IoT Relaying	Cellular Relaying
Energy constrained	Plugged into constant power source
Currently Nonstandardized	Standardized (LTE L1, L2 and L3 relays)
Dynamic topology	Mostly fixed topology
Multihop-enabled	Mostly dual hop to the nearest BS
Hierarchical	Hierarchical
Planned or ad hoc deployment	Mostly planned deployment
For mobile relays there is no mainstream, adopted mobility management strategy	Mobility of UEs managed through network controlled handovers

and a description of relaying strategies (amplify-and-forward, decode-and-forward and compress-and-forward protocols) are also given in this section. In Section II, challenges of relaying in the IoT are also highlighted as a forerunner to the approaches in the literature to solve these challenges. Section III thoroughly reviews the approaches to the challenges of relaying in the IoT adopted in the literature. In this section, there is a subsection that focuses on specific research

solutions, such as edge caching and NOMA. Section IV is dedicated to the literature that has considered machine learning and AI approaches for IoT relaying, and in Section V, we describe key application areas of relay-enabled IoT networks. We conclude the paper in Section VII after detailing the open research questions in Section VI.

II. A SHORT DESCRIPTION OF RELAYING IN THE IoT

In this section, we give a general background on relaying and then go on to explain in brief detail the popular relaying strategies. Against this backdrop, IoT relaying is described. A key feature in this section is the categorization of relays in the IoT into classes to enhance the discussion in the subsequent sections.

A. BRIEF BACKGROUND ON RELAYING

The idea of using an intermediary device or cluster of devices to assist the transmission of information for another device or set of devices (referred to as source(s)) has been shown to offer several gains and has been studied for a long time in academia and applied in industry. Extensions of the basic three-node network (having a source node, destination node and a relay) have also been discussed in the literature. Early work on the relay channel was reported in [32], where

the classic three-terminal transmission setup was introduced and its capacity bounds were presented. The capacity of a Gaussian degraded relay channel was studied in [33]. This classic three-terminal communication channel has also been extended to include multiple relays [34], multiantenna relays [35], and buffered relays [36]. In [37], the diversity gain obtained when a source and a relay cooperate to transmit information is demonstrated. Cooperative communication is possible when the source-destination and the source-relay-destination links are available. In such a case, there must be a suitable combining strategy at the receiver. Cooperative communication also occurs when multiple sources jointly transmit each other's information such that all the sources act as relays for a single source iteratively. In scenarios where the source-destination link is unavailable, relaying can still be achieved without the relay cooperating with the source device. When multiple relays are deployed in a network and multihopping from source to destination is enabled, the problem of selecting suitable routing protocols arises. Routing is a rich research area; therefore, the choice of routing protocols and the taxonomy of routing protocols are outside the scope of this survey.

B. RELAYING PROTOCOLS

Relays perform operations on the signal they are meant to retransmit. Based on the operations that relays carry out on their received signals, relaying protocols can be categorized as follows:

1) AMPLIFY AND FORWARD (AF)

In the amplify-and-forward protocol, the relay retransmits an amplified version of the signal it receives from the source. The simplicity of implementation of the AF strategy makes it attractive, although it has the downside of noise and interference amplification.

2) DECODE AND FORWARD (DF)

Here, the relay extracts the received signal and re-encodes it before re-transmission. In the DF protocol, a condition for relay selection can be the successful decoding of the received signal by a relay.

3) COMPRESS AND FORWARD

In the DF strategy, the relay can decode the received signal, whereas the compress-and-forward protocol allows the relay to send a compressed/scaled-down version of the received signal to the destination. In the reviewed literature for this paper, AF and DF relaying strategies are the most widely used protocols.

The performance of AF and DF relaying protocols has been studied in cellular networks as a coverage extension strategy [38], cognitive radio networks as a cooperative sensing strategy [39] and wireless sensor networks (WSNs) as a coverage extension and energy-saving strategy [40]. Similar to WSNs, IoT devices are power constrained, and deploying relays for forwarding observations from end devices to

gateways can help IoT networks reduce their overall network energy consumption. Both AF and DF strategies can be applied in IoT networks, although the reduced complexity of AF relaying makes it a preferred choice.

C. RELAYING TOPOLOGIES

In wireless networks, relays can assume various topologies depending on the nature of the applications. Fixed relays are common in mobile communication networks and in wireless sensor networks. Network designs with fixed relays require prior planning before deployment and tend to be rigid. Relaying topology-based fixed nodes are easier to model but challenging to modify. On the one hand, relaying topologies based on mobile nodes are more dynamic and adaptive to changes in network structure. With increasing interest in UAVs, the performance of relay topologies based on such high mobility nodes has been analyzed. UAV-based relays in IoT nodes are flexible and can be quickly deployed in an emergency. In this paper, Section III-D is devoted to UAV relaying in IoT networks.

D. RELAYING IN THE IoT

Relays in the IoT can be categorized based on various parameters. Relays can be categorized as being network-provided or user-provided entities. In network-provided relays, the relay nodes are part of the network rollout, whereas user-provided relays are user-owned devices that can opportunistically serve as relays. Relays in the IoT can also be dedicated, where the nodes are originally designed to forward data or they could be opportunistic where their presence in a network is fluid. Furthermore, relays can be grouped as mobile relays or fixed relay nodes. The boundaries of these classifications overlap because fixed network-provided relays can also be mobile, as in the case of an access point mounted on a vehicle. The fixed and mobile relay categories are broader and more encompassing. A diagram showing various IoT classes is shown in Fig. 1, and our classification of relays is given in Fig. 2. In network-provided relays, a base station or a fixed relay node handles the allocation of radio resources and coordinates interference, as in the case of LTE-A relays [41],

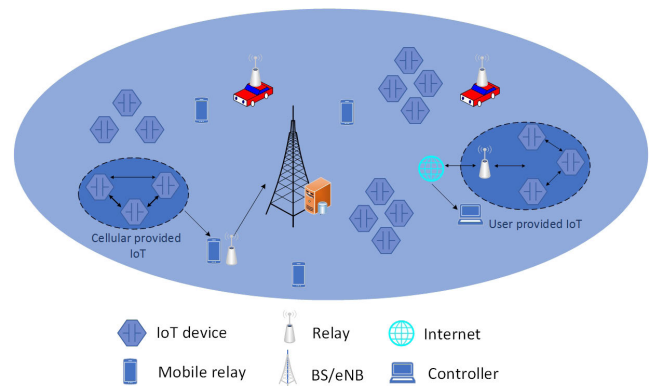


FIGURE 1. Cellular-provided and user-provided IoT.

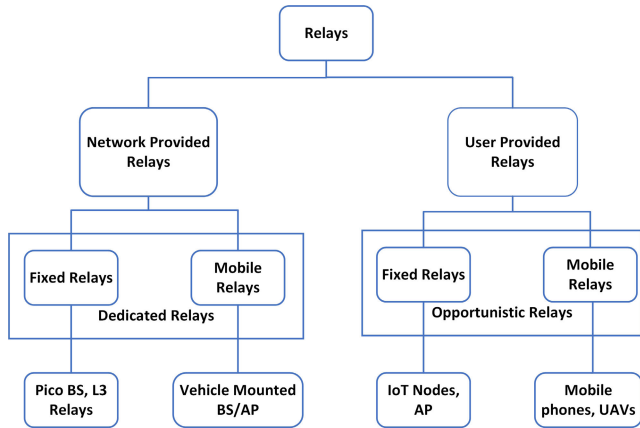


FIGURE 2. Classification of relays.

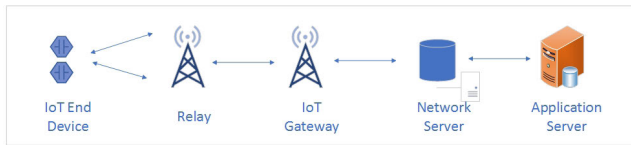


FIGURE 3. Possible relay-aided IoT network architecture.

and pico-BSs act as relays to enable communication between IoT devices [42].

The addition of relays in IoT networks can improve the reliability of networks, increase network lifetime, save energy through reduced transmit power of the end device, and decrease the cost of multiple gateway deployments, among other gains. It is still debatable whether relays in IoT networks should be IoT end devices modified to serve as relays or

whether they should be gateways that forward IoT end device observations to the network in a multihop fashion. In the literature reviewed for this paper, the form of relays for the IoT depends on the design goals of the research paper. A possible architecture for a relay-assisted IoT network is shown in Fig. 3.

Despite the gains and benefits of having relays in IoT networks, which include energy efficiency, diversity gain and increased lifetime of the network, various hurdles can impair the implementation of relaying in IoT networks. In this section, such challenges are studied. A taxonomy of the challenges of relaying in the IoT and the approaches given in the literature to solving them is given in Fig. 4.

1) ENERGY CONSTRAINT ON RELAY NODES

One of the design goals of the IoT is energy efficiency. To achieve this goal, there are limitations on the amount of energy that IoT end devices can consume. In fact, some connectivity technologies for the IoT (such as LoRa and SigFox) have a limited duty cycle of approximately 1%. Deploying relays in IoT networks should not significantly increase the energy consumption of networks. In uplink communication, relays consume energy when (1) listening for signals from IoT end devices and (2) forwarding signals to the gateways. Although with the deployment of relays, the transmit power of IoT end devices can be reduced, there are trade-offs between the increased reliability that relays can offer vis-a-vis the power consumption of relays. Whereas gateways are mostly connected to a constant power source and end devices are battery-powered, relays, on the other hand, need power sources that allow them sufficient capacity to forward

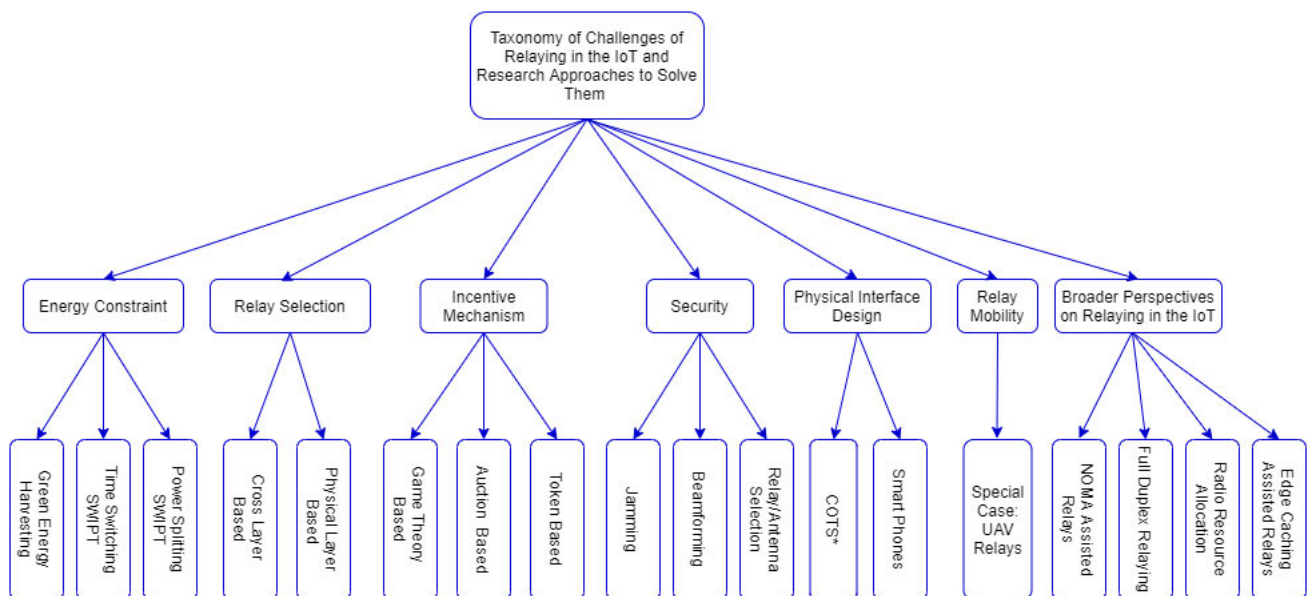


FIGURE 4. Taxonomy of challenges and approaches in IoT relaying research. *Commercial off-the-shelf.

received signals from IoT end devices without being tethered to a power source such as a gateway.

Approaches to addressing the energy constraint of IoT relays have focused on enabling relays to harvest energy from the transmit signal or from other sources (such as solar) in the environment. Research has proposed simultaneous wireless and information power transfer (SWIPT) methods for IoT relays, whereas little research emphasis has been placed on the use of other forms of energy to boost the residual energy of relays. Despite the research efforts on SWIPT in IoT relaying, implementation challenges can hinder actual testbed evaluations. For IoT networks that use already available cellular infrastructure, energy availability may not be a major constraint given that there may be a constant power source. Subsection III-A presents a survey of SWIPT techniques for relay-aided IoT networks in the literature. Energy constraints at relays can also be addressed by designing IoT architectures with energy-efficient relay nodes. Such architectures limit the amount of transmit power of the relay or allow the relay to only participate in message forwarding instead of combining sensing and message forwarding.

2) RELAY SELECTION

Relay selection is a problem that comes up when there is more than one potential relay available to forward data between an IoT end device and a gateway/IoT end device, as demonstrated in Fig. 5. A straightforward method would be to select a relay for which the data rate of the source-relay-destination (S-R-D) link is maximum, i.e., for N relays, where the data rate of the S-R-D link of the i_{th} relay is given by R_i , and the selection criteria are given by:

$$\max_{1 \leq i \leq N} (R_i) \quad (1a)$$

A selection criterion is key in choosing a relay. The problem of relay selection becomes more complicated when more than a single criterion is used to select a relay. Using the link quality alone as in equation 1 as the selection criterion can ignore the battery life of the relay and other upper layer performance metrics. Similarly, for buffer-aided relays, if only the link quality is used for relay selection,

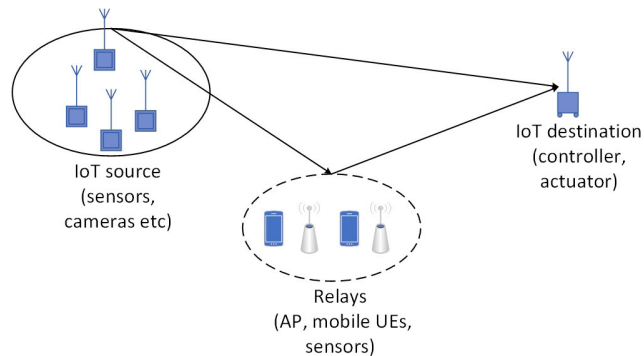


FIGURE 5. Relay selection setup.

the relay buffer state can be ignored, leading to packet losses. Hence, for relay-enabled IoT networks, relay selection is a challenge. IoT networks are often designed with a centralized architecture where IoT end devices connect to a gateway/base station in a star topology. When relays are introduced into IoT networks, a problem to address is whether to use a centralized relay selection algorithm where the network server or gateway selects a relay or whether end devices should select relays in a distributed fashion, an approach that does not require complete knowledge of channel state information [43]. In this survey, the relay selection algorithms proposed by recent research contributions for relay-assisted IoT networks are reviewed in subsection III-B.

3) INCENTIVE MECHANISM

The 'things' that make up the IoT may not have self-interested motives, so in selecting them as relays, incentives may not be a priority. When these things are carried around by humans, for example, mobile devices and cars (in the case of vehicle relaying for smart transport), there then needs to be a way of motivating relay participation. In such cases of human participation, end devices can use short-range connectivity solutions, such as BLE or Wi-Fi, to send data to participating human-held relays that help forward received data to gateways or access points in a time-slotted manner. Selfish behavior among relay-capable devices owned by humans can deteriorate the performance of IoT networks because of the humans in the loop. This is because such users may not be willing to use their devices to forward observations of IoT end devices and thus lead to dropped packets. Designing incentives that are commensurate with the relay services offered is a challenge for relaying in the IoT given the nature of data transmitted by IoT devices. IoT sender nodes that are observing the environment may not be transmitting regularly, and the data sizes may not be large enough to warrant high-value incentives to spur relay participation. Incentive mechanisms also pose a challenge for standalone IoT networks because where there are many noncompatible proprietary IoT networks, porting or moving the incentive of one network to another becomes cumbersome. Popular incentive mechanisms used in other wireless networks fall into the categories of game theory-based and nongame theory-based approaches.

4) SECURITY AND TRUST

The broadcast nature of wireless networks makes them susceptible to security infractions. Relays have been shown to increase the secrecy rate of wireless networks [44] without the use of higher-level cryptography functions such as the exchange of secret keys. However, the presence of user-owned relays (machines, objects, smartphones, vehicles, etc.) in IoT networks poses a security risk. Such risk arises when the relay is untrusted. Untrusted relays, although helpful in information forwarding, can be malicious. This can be problematic when the data to be forwarded are confidential.

For private information such as patient data in medical IoT networks, unauthorized access to such data constitutes a security challenge. Physical layer security has been proposed to ensure that malicious eavesdroppers and untrusted relay nodes do not compromise the network. Cryptographic approaches have also been proposed where keys are shared between the relay nodes and the IoT nodes. Some low-power technologies, such as LoRaWAN, already have end-to-end data encryption schemes built into their IoT network [45]. However, for the work in this survey, current research works on physical layer security for relay-assisted IoT networks are reviewed. Cryptographic approaches are beyond the scope of this paper.

5) MOBILITY

Where relays are not stationary infrastructure relays, their positions in a network vary, and this variation can lead to loss of connection for the stationary IoT end devices that the relays are meant to support. To keep tabs on mobile relays in a network, the relay devices can be registered with the network to ensure authentication and provide incentive action. Where such registration is done, mobility apart from creating connectivity challenges will also cause redundant registration with the server. Since the nodes are mobile, some may not complete the transmission of data and thus can leave the network coverage area, leading to the storage of redundant data. This can be overcome by setting a time-to-live threshold for registered relays to assist in IoT communication. Where relay nodes are human-held devices, incentives can help to motivate relaying and stem random mobility. Managing relay mobility for IoT devices, especially when the relays are third-party owned devices, is a challenge. For cellular network-based IoT, mobility management through handovers is supported by the network. The research contribution in [46] studied time-varying IoT networks assisted by relays with time-varying locations. Recently, there has been a surge in research interest in UAV relays. UAV relays are not only mobile but are elevated above the IoT nodes they serve. Hence, they present a good example to study relay mobility in IoT networks. In Section III-D, a thorough review of research works in UAV relays in IoT networks is presented.

6) PHYSICAL INTERFACE DESIGN

One key challenge of relaying in the IoT is the physical interface design of the relay. In cellular networks, infrastructure relays are scaled-down base stations to which mobile devices can associate for data forwarding. The challenge of designing relays in the manner of cellular networks will imply having additional low-power gateways. This adds to the cost of IoT network rollout. Conversely, using end devices as relays would require some modification to allow an increased receive window and an additional radio interface to allow two-way communication. Subsection III-E surveys the approaches to practically design and deploy relays in IoT networks.

III. PROPOSED APPROACHES TO THE CHALLENGES OF RELAYING IN IoT

In the previous section, the various challenges that relay-enabled IoT networks face have been highlighted and explained. In this section, a review of the approaches proposed in the literature to address these challenges is presented.

We first discuss energy harvesting solutions for relay-enabled IoT networks before reviewing relay selection algorithms proposed for IoT networks. Incentive mechanisms proposed for IoT relays and secure relay-enabled IoT networks are discussed next. These are followed by a survey of papers focused on other broader concepts such as radio resource allocation, edge caching, NOMA and full-duplex relaying in IoT networks. There is also a subsection on relay physical interface design.

A. ENERGY HARVESTING (EH) IN RELAY-ENABLED IoT NETWORKS

To cater to the energy needs of relays in IoT networks, some contributions have proposed the use of the energy harvested from wireless signals through wireless power transfer (WPT). In WPT, the relay either replenishes its embedded energy source using the transmission from a dedicated power beacon (PB) transmitter or extracts energy from the source IoT device for which it is relaying while receiving data signals as well (Fig. 6). The latter approach, which is called simultaneous wireless information and power transfer (SWIPT), is mainly achieved through a power splitting (PS) method, a time switching (TS) method or a hybrid of both modes at the relay. Antenna switching and separate receiver architectures are other ways of achieving SWIPT, although TS and PS are mostly used in research works on IoT relaying. Practically, it is not feasible to harvest energy and decode information concurrently, hence the use of splitting and switching techniques to achieve SWIPT. Apart from electromagnetic radiation, solar energy and vibration are other sources from which relay nodes can harvest energy. In this subsection, contributions to energy harvesting for IoT relays are discussed and categorized. A summary of approaches to energy harvesting-based relay-enabled IoT networks is presented in Table 4, and the key features of TS and PS are given in Table 5.

1) POWER SPLITTING IN SWIPT RELAY-ENABLED IoT

When SWIPT is implemented using PS, the relay divides the power received from the source device into two portions; a portion is used to replenish the energy reservoir of the relay, whereas the remainder is used for information processing and forwarding. Power switching has been considered for IoT networks with SWIPT relays [47], [48] and [49].

Asiedu *et al.* [47] proposed a PS ratio for SWIPT relays without external energy sources in a downlink multihop IoT network using DF protocols at the relays. Source transmit power minimization and system throughput maximization problems were formulated subject to energy and power ratio

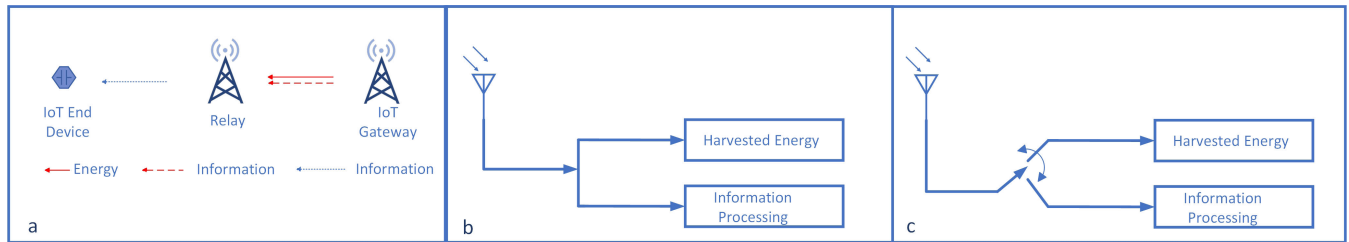


FIGURE 6. (a). Relay energy harvesting from downlink transmission (b). SWIPT using power splitting (c). SWIPT using time switching.

TABLE 4. Summary of energy harvesting-based relay-enabled IoT networks.

Harvesting technique	Article	Approach
SWIPT (PS)	[47]	PS ratio optimization
	[48]	PS ratio optimization
	[49]	PS ratio optimization
SWIPT(TS)	[50]	Power and subcarrier allocation
	[51]	TS ratio and relay power optimization
	[52]	Transmission time optimization
	[4]	Outage probability minimization
	[53]	Sum-rate maximization
	[54]	Outage probability and Ergodic probability analysis
SWIPT (Dual PS and TS)	[55]	Error probability analysis
	[56]	Outage probability analysis
	[57]	Outage probability analysis
Green energy harvesting	[58]	Distortion reduction maximization
	[42]	Bandwidth and power optimization

constraints. The authors demonstrated the power splitting ratio that can result in reduced source transmit power by performing simulations and offer an improved system data rate. It was also shown that an optimal number of relay nodes exists for a multihop half-duplex IoT system. An optimal PS ratio was also proposed for a case where the nodes had imperfect CSI. Analogous to most research efforts in SWIPT, the work in [47] dwelt on optimizing the PS ratio.

In relay networks where the energy that a relay uses for information forwarding comes from harvested RF energy, the destination node is treated as an information receiver. Not so in [48], where a relay powered by harvested energy from

TABLE 5. Features of power splitting and time switching.

Power Splitting	Time Switching
EH and Information reception happens simultaneously	Switches between EH and Information reception
Requires additional hardware to divide the received signal into harvested energy and information decoding	No additional hardware for TS apart from a switch at the receiver
EH and Information decoding can be jointly optimized	TS ratio can be optimized
Consumes less time resources	Harvest more power
Lower SNR for information decoding [55]	Shorter frame length for information transmission [55]

the source device forwards data to one destination and RF energy to a second destination. The research also used the Lagrangian multiplier method to solve an energy efficiency maximization problem subject to harvested energy at the second destination node. This is done to obtain the optimal transmission strategy of the relay, although the relaying strategy is not clear and the work assumes perfect knowledge of the associated channels. In formulating the optimization problem, the relay transmit power is not bounded by an upper limit.

In [49], Zou *et al.* considered an IoT network enabled by a SWIPT relay using the PS protocol. The work presented an outage probability analysis of a proposed optimal PS with relay selection. Hence, a relay that has a PS ratio that maximizes the capacity of communication is selected. Through simulation and theoretical formulations, the authors show the gains of employing their approach over the equal PS ratio method. The proposed approach may be biased toward allocating more power to signal decoding than to energy harvesting and thus ignores the residual power needs of the energy harvesting relay. The proposed PS ratio technique was tested in DF and AF relay networks. The outage performance of the EH with AF relays consistently outperformed that of DF relays for various numbers of relays, SNRs and energy conversion efficiencies.

Key Insight: Downlink system models are considered in [47] and [48], where the SWIPT relay harvests energy from the transmission of the base station/gateway in one time slot and uses the next time slot to transmit information to the IoT end device. Such a time-slotted approach where the

relay is a half-duplex relay is also used by Y. Zou *et al.* [49]. The objective of the work in [47] and [49] includes optimizing the PS ratio to improve the system-level data rate and outage probability, respectively. The assumption of the availability of perfect channel state information (CSI) in [49] is extended in [47] to consider the existence of CSI errors. The surveyed works in PS SWIPT use simulations, whereas in [47] and [49], closed-form expressions are derived for the optimal power splitting ratio. The considered works similarly assumed that the relay has a battery that stores harvested energy, although [49] actually characterized the stored energy. The optimal PS ratio improves the system rate and reduces the energy consumption of a relay-enabled IoT network over a fixed PS ratio. Moreover, for a fixed data rate, the energy conversion efficiency of a SWIPT relay limits the outage probability of a relay IoT network.

Implementing SWIPT using TS has also been studied in relay-enabled IoT networks.

2) TIME SWITCHING IN SWIPT RELAY-ENABLED IoT

Relays that use TS-based SWIPT alternate between energy harvesting and signal forwarding, as shown in Fig. 6c. There are several research works on the IoT that study TS in SWIPT relays [4], [51]–[54].

The papers on relaying in IoT networks in which the relay uses the time-switching technique for energy harvesting can be loosely grouped into two categories. These are dedicated PB transmitter-based [51]–[53] and nondedicated PB transmitter-based [4] and [54] approaches.

Optimal solutions are derived for a sum-throughput maximization problem in [51], where a relay's energy need is met by harvested energy from a dedicated access point (AP). In the modeled network, the AP is the receiver of the transmissions of IoT end devices through the relay. The research work showed that the fairness performance and throughput of the proposed system depend on the scheduling of IoT end device transmission. Reference [52] derives closed-form solutions for transmission time minimization problems. The presented system model involves a dedicated power beacon (PB) transmitter and an IoT source device that backscatters PB signals to a relay and a destination IoT device (gateway). In so doing, cooperation between the source device and the relay is enabled. The proposed relay cooperation scheme offers improved throughput in comparison with a case where the relay has an embedded energy source. Both works [51] and [52] consider system models with a dedicated PB transmitter serving a single relay network. This is advantageous because more energy can be harvested from a PB transmitter than from a low-duty-cycle, energy-constrained IoT end device. The proposed relay harvesting approach in [51] does not enjoy the cooperative gain proposed in [52]. Another difference between the two works is that the relay in [52] switches between information forwarding, backscattering and energy harvesting, whereas in [51], the relay switches between energy harvesting and information forwarding.

A novel relaying scheme is presented in [53], where gateways are powered by the energy harvested from AP relay messages between the AP and batteryless IoT devices. The work derived closed-form solutions to the problem of maximizing a formulated sum-rate maximization problem. This was accomplished by jointly optimizing the time scheduling, energy beamforming and power allocation at the AP. The proposed scheme offers system throughput gains in comparison to a fixed time allocation approach. Although both [53] and [52] enable backscattering between an IoT device and the relay, in [53], the direct path between the IoT source device and the receiver is considered absent.

Unlike the work in [52] and [51], where one-way communication between the relay and the destination is studied, [4] derived closed-form expressions for the outage probability of a 2-way relaying setup with Nakagami-m faded channels. In the setup, two secondary IoT devices act as DF relays that depend on harvested energy from a pair of primary users and forward information to them. The accuracy of the derived analytical expressions is verified by simulations to demonstrate the effect of channel fading parameters on the system outage probability. Moreover, the frame structure of the proposed setup allows switching between energy harvesting and information processing. Although some practical IoT connectivity technologies, such as Weightless [59], enable cognitive radio technology, the limited transmit window of some IoT applications can be a drawback for two-way communication. Similarly, Nguyen *et al.* [54] presented the performance of a two-way relay-assisted IoT network. The work does not assume the availability of a dedicated PB transmitter since the relay harvests energy from the transmission of the source IoT device. It extends the two-way relay setup to consider a Rician fading channel between the source and destination IoT devices, deriving outage probability expressions for both delay-tolerant and delay-limited cases. This is useful considering the varied delay requirements of IoT applications. Performance metrics such as outage probability, ergodic capacity and throughput are studied for various system parameters, and their performance also proves the accuracy of the theoretical derivations.

Key Insights: In the reviewed contributions to IoT relaying where the relay uses TS-based SWIPT, dedicated PB transmitters are assumed in works that consider one-way relaying, and the system performance is analyzed for parameters such as throughput [51], [52], [54] and ergodic capacity [54]. Theoretical analysis mostly accomplished through closed-form solutions to formulated optimization problems is the approach that the reviewed papers use. Moreover, a DF relaying protocol is also adopted by the surveyed papers. The relaying protocol is key to attaining target throughput in SWIPT relay IoT networks. This is because DF relays tend to offer improved performance relative to AF relaying for parameters such as throughput, outage probability and energy consumption. Combining PS and TS protocols can ensure that the gains of both protocols are derived by the relay-enabled IoT network.

3) DUAL POWER SPLITTING AND TIME SWITCHING IN SWIPT RELAY-ENABLED IoT

PS and TS SWIPT protocols have gains that can be exploited by using both protocols together. Certain research works have concurrently considered PS and TS protocols for SWIPT relays in IoT [55]–[57]. Hu *et al.* [55] study the reliability performance of a hybrid PS-TS SWIPT-enabled IoT network in the finite blocklength regime. Combining TS and PS was shown to offer better error probability performance than using each protocol individually. Using TS-based SWIPT in relays offers improved throughput and outage probability over PT-based SWIPT [56]. Moreover, jointly optimizing the blocklength allocation and SWIPT parameters results in a slight improvement in error probability performance over nonhybrid SWIPT protocols [55]. Furthermore, average throughput analysis is performed in [60] for an IoT network assisted by a relay node selected based on the source-relay data rate. Unlike most works, the paper considered finite blocklength codeword transmission and proposed an optimal and suboptimal design of the transmission data rate based on an approximated closed-form expression of the throughput of the IoT network.

Relays in IoT networks are often modeled as nodes that are nondata generating and thus only wait for data from a source that requires forwarding services. Where relay nodes are modeled as data-generating, their data transmission is usually assumed not to occur during the forwarding phase of relay communication. A case where a relay has data to transmit during its forwarding phase might occur when the source and relay target the same destination device with their distinct signals or where both the relay and the source devices target separate destinations. For the latter case, there has to be a way to tell each destination to treat as noise or interference the signals not intended for it. Such an indicator can be added to the overhead when signaling. Additional overhead to inform the destinations can be avoided by using nonorthogonal multiple access (NOMA), which allows the superposition of separate signals and allocating power to the separate signals based on the link quality [57]. In [57], the effect of interference is studied for a relay-aided IoT network in which a NOMA-based relay harvests energy from the transmission of the source IoT device. TS and PS are considered for the half-duplex single relay that not only forwards the source signal to a destination but also has its own signals to send to a separate destination. The work employs a golden search method to solve outage probability and throughput optimization problems. This approach assumes that the relaying node has a signal to send concurrently with the source devices data.

Key Insights: Using a hybrid of TS and PS protocols can help exploit the advantage each offers by switching to the TS protocol when more energy is needed and switching to PS when the transmission is delay-sensitive [55]. The downside of a hybrid approach may be hardware complexity, and this has not been studied. Combining NOMA and EH can result in improved network throughput [57]. The

NOMA-enabled relaying IoT network is considered separately in Section IV-F.

Studies have been performed on relay nodes harvesting energy from sources other than wireless signals. As future networks are envisaged to be more energy-efficient, employing renewable energy sources for energy harvesting relays is also attractive.

4) GREEN ENERGY HARVESTING-BASED RELAY-ENABLED IoT

SWIPT techniques are not the only approach to energy harvesting studied in relay-enabled IoT. Harvesting energy from sources other than RF, such as solar energy [42], [58], has also been studied.

In [58], the authors present a search method for obtaining the optimal relay selection and power allocation for relays assisting sky cameras in an energy harvesting wireless sensor network. The proposed search algorithm is designed to solve a distortion reduction maximization problem subject to energy constraints. Simulations have demonstrated the improved outage performance of the proposed algorithm over a so-called nearest relay selection algorithm. However, the relaying protocol is not clear, and the complexity of the algorithm could increase with an increased number of relay hops. Similarly, [42] considered harvesting solar energy to power fixed pico BS relays. Different from the research works on SWIPT relaying that assume batteryless relays, a dual battery architecture is proposed in [42], and the architecture is shown through simulations to result in higher residual energy compared to single battery relays. Providing additional solar-powered batteries for IoT relays incurs costs, especially for standalone private application-specific IoT deployments.

Key Insights: Energy-efficient relaying is important in relay-enabled IoT networks since a relay uses its energy resources to cater to the data forwarding needs of neighboring IoT devices. Hence, harvesting energy is a key strategy to maintain the battery energy of relay nodes. In a cellular-provided IoT network, where a fixed relay is used, a hybrid energy source that uses both on-grid power and harvested energy can be used to harness the green energy potential of energy harvesting [42].

B. RELAY SELECTION IN RELAY-ENABLED IoT NETWORKS

The use of relays provides diversity gains and energy efficiency improvement because a source IoT device may not need to transmit at full power to reach a gateway or destination IoT device. The lifetime of an IoT network is also enhanced when relays participate in data forwarding. To exploit these gains, schemes to select a relay or a cluster of relays to assist in data forwarding are necessary. In the works reviewed for this survey, various relay selection techniques were proposed, and their results are herein discussed. Relay selection algorithms proposed in the surveyed research contributions for relaying in IoT networks can be loosely classified into (a) physical layer selection algorithms and

TABLE 6. Relay selection techniques in IoT networks.

Article	Objective	RS Metric	Protocol Layer	Relay Strategy	Approach	Mode
[49]	Minimize outage probability of the S-R-D link	Power splitting ratio	PHY	AF and DF	Simulation and analysis	HD
[61]	Minimize outage probability	R-D CDI and Residual energy	✓	VG-AF	Analysis and Simulation	HD
[62]	Outage probability minimization	Convergence time of relay link	PHY	AF	Theoretical analysis and simulations	HD
[63]	Maximization of network resource availability	Received power	PHY	Not clear	Simulation	HD
[46]	Minimize data latency and packet loss risk	latency and link reliability	MAC and PHY	Not clear	Simulation and analysis	HD
[64]	Service availability maximization and battery life improvement	CSI, relay battery energy relay distance to BS	PHY	No relay processing	Simulation	HD
[65]	Destination's received SNR maximization	S-R-D CSI	PHY	AF	Simulation	HD
[66]	Maximum total transmission time minimization	S-R data rate	PHY	Not clear	Simulation	HD
[67]	Security-reliability trade-off optimization	Secrecy capacity of relay link	PHY	DF	Theoretical analysis and simulation	HD
[72]	Maximize data rate and CDF of the channel	Data rate and CDF of the channel gain	PHY	AF	Simulation and analysis	HD
[73]	Maximize throughput	Link capacity and buffer state	PHY and MAC	DF	Simulation and analysis	HD
[80]	Minimize secrecy and link outage probabilities	BSI and CSI	PHY	AF	Simulation	HD
[75]	Outage probability minimization	Relay buffer state and CSI of relay link	PHY and MAC	DF	Theoretical analysis and simulation	HD
[76]	Latency minimization	Transmission Probability	PHY	Not Clear	Simulation	HD
[81]	SOP minimization	R-D Data rate	PHY	AF	Simulation	HD
[74]	OP and delay minimization	S-R-D Data rate and Buffer occupancy	PHY and MAC	DF	Analysis and simulation	HD
[30]	Energy minimization	S-R Distance and energy consumption	PHY	Not clear	Simulation	HD
[82]	Secrecy capacity maximization	R-D/ R-E channel gain ratio	PHY	AF	Simulation	HD

(b) cross-layer selection algorithms. In the former approach, the research works focus on selecting a relay based on the physical layer parameters of the participating links, whereas in the latter approach, the authors employ additional parameters from upper communication layers to determine the selection metric. In this section, a review and classification of proposed approaches in the literature are given. A summary of works on relay selection techniques for IoT networks is given in Table 6.

1) PHYSICAL LAYER-BASED RELAY SELECTION

Selecting relays based on a measured physical layer parameter has been studied for IoT networks in [30], [49], [61]–[68]

The lifetime of relay-enabled networks depends on the residual energy of the relays, and if a relay is selected solely using the link quality as the metric, the network may experience outage if the relay's energy source is severely drained. Kawabata *et al.* [61] proposed a relay selection algorithm that is based primarily on three metrics: 1) the residual energy of relays, 2) the channel distribution information (CDI) of the channel gain between the relays and the destination IoT device and 3) the distribution of the distance of each relay

from the destination IoT device. Using stochastic geometry for modeling the IoT network, the paper derives the closed-form outage probability for the network, and through numerical analysis and simulations, the proposed approach is shown to offer improved outage probability performance over a selection scheme that uses the channel gain mean. However, the algorithm proposed in [61] falls below an instantaneous CSI-based selection approach in outage probability performance. The relaying protocol employed is the variable gain amplify-and-forward protocol. Zou *et al.* [49] proposed a relay selection scheme that selects a relay that has a power splitting ratio that best maximizes the overall channel capacity of an IoT network. The scheme showed improved outage probability performance over an equal power splitting ratio selection algorithm. Both [61] and [49] consider energy harvesting IoT networks where the relay splits the received signal from the source IoT device into energy for signal decoding and energy harvesting. Both also use outage probability as their performance evaluation metric.

The availability of mobile relays within the forwarding distance of source and destination IoT devices is advantageous, as their presence can be exploited to improve the

performance of an IoT network. However, since the movement of these mobile relays is random, the probability of outages can increase when they move out of the coverage of the IoT sender device. Hence, determining a mobility range for mobile relays [62] can help exclude some relay-enabled devices from the potential relay set. In [62], an iterative steepest descent algorithm that solves an outage probability minimization problem (to obtain the optimal relay position and relay transmit power) is proposed. A relay selection algorithm is also proposed that selects a relay link for which the solution to the optimization algorithm converges fastest. In formulating the optimization problem, there is a constraint on the mobility of the relay, which is not counterintuitive since if a relay is too far from the source and destination IoT devices, the outage probability of the network will increase. However, it is not clear how the mobility range is obtained.

For IoT deployed in a cellular network, the base station can be tasked with allocating fixed relays or mobile relays to assist in data forwarding for IoT devices. In such a case, relayed communication can use already available technologies such as D2D and M2M communication. Relay-enabled IoT deployed within a cellular network was studied in [30], [63], [64], and [66]. The IoT deployed within a 5G heterogeneous network is considered by Dao *et al.* [63]. In the considered setup, an IoT source that experiences intercell interference uses D2D communication to discover nearby idle IoT terminals. These discovered IoT devices then report the received power from the interested IoT source to a central eNB, which assigns a suitable IoT device and a pico BS with a sufficient resource block as relays for the IoT source device. The proposed selection method offers increased network throughput and number of served IoT devices. However, since the approach uses D2D communication, D2D discovery and link establishment increase the overhead of relay transmission. Channel state information, battery energy level and distance from the BS are the metrics employed by Lianghai *et al.* [64] to select relays for cellular IoT communication. The proposed system model initially clusters nearby devices using K-means clustering and determines their transmission mode (either cellular or D2D) based on the measured performance metric. The relay selection approach is centralized and may result in increased overhead.

Specifications for NB-IoT, a low-power IoT technology developed by 3GPP, have been created for cellular network-provided IoT [69]. Using NB-IoT, the work in [30] proposed a relay selection algorithm for a formulated total network energy minimization problem. The algorithm selects relays in a manner in which the relay with the least energy consumption in comparison to the energy consumption of the direct link is selected. Moreover, for the selected relay, the source-relay (S \hat{R}) distance must be less than the relay-destination (R \hat{D}) distance. The proposed relay selection algorithm was shown to consume less energy than direct communication. Considering a cellular-based IoT network, Hsu *et al.* [66] proposed a relay transmission order, data partitioning method and a relay selection algorithm for a

formulated optimization problem targeted at minimizing the maximum total data transmission time of the IoT network. The source IoT device selects a relay set for which the S-R data rate exceeds the relay \hat{B} base station data rate. The proposed selection algorithm is shown to offer reduced transmission time and is suitable for mission-critical IoT communication. It requires perfect channel knowledge and would find application in cellular-based IoT with a computationally capable central entity (that is, a BS).

When perfect CSI is not available, channel uncertainty can affect the channel estimates and consequently the achievable data rate of an IoT setup. For such a system model where channel uncertainty is considered, an adaptive transmit power strategy that is channel uncertainty-aware can be employed to overcome the effect of channel uncertainty [70]. In modeling channel estimation errors, an approach is to present it as a Gaussian distributed random variable that is added to the channel estimate [67], [71]. In [67], a channel estimation error-aware relay setup is presented. The work proposed a way to select devices from a relay set in a manner that maximizes the capacity of the S-R-D link in the presence of an eavesdropper with better link quality than the S-R-D link. It also proposed that a jamming device can be selected to transmit artificial noise to limit interception of target signals by the eavesdropper. However, transmitting a jamming signal for closely positioned devices may require knowledge of the artificial noise sequence at the destination IoT device and thus contribute to overhead. A machine learning (ML) selection technique was proposed for an IoT network assisted by multiple relays in [65]. Channel coefficients were used as data for model training, and the so-called iterative sparse relay selection algorithm was used for relay selection. The selection metric is basically the channel coefficients, and the paper considers jointly optimizing the received signal-to-noise ratio (SNR) at the receiver and the beamforming coefficients at the relays. Using ML is attractive considering that the IoT will interconnect many devices, resulting in considerable data generation, but the resources required for ML implementation may only be suitable for centrally controlled IoT networks.

Two relay selection schemes were proposed by Farooq *et al.* in [68], namely, a selection scheme that selects a relay nearest to the IoT source device and a selection scheme that selects a relay that enhances the progress of forwarded data toward the destination. The work studied a massive IoT network assisted by multihop relays and used the Poisson point process to model the distribution of the considered devices. The numerical results showed that the strategy based on nearness to the transmitter resulted in higher transmission success probability, a result that highlights the gains of short hops. Moreover, the research contribution in [68] also showed that the spatial frequency reuse increased as the carrier sensing threshold was increased, an intuitive conclusion.

Key Insights: Relay selection algorithms in the surveyed literature that are based on physical layer parameters have

mostly used CSI- or CSI-related metrics for relay selection except in [49], where the power splitting ratio was used. In using CSI, only [61] considered statistical CSI instead of exact CSI. The availability of instantaneous CSI can help improve diversity gain [61], although in practical IoT networks, acquiring CSI can be overhead intensive. Furthermore, relay selection schemes formulated as joint optimization allow for better performance trade-offs when compared to single optimization schemes.

In designing relay selection algorithms, physical layer parameters such as channel gain, data rate, and secrecy capacity can be used to choose relays from a set of idle nodes. Physical layer parameters relate directly to physical layer performance metrics, although the performance of relays can also be affected by upper layer conditions such as the queue state information of the buffer of a relay or the delay in a relay link. Therefore, cross-layer approaches are necessary to capture layer-specific performance metrics.

2) CROSS-LAYER-BASED RELAY SELECTION

In [46] and [72]–[76], cross-layer relay selection algorithms were proposed for relay-enabled IoT networks.

Redhu *et al.* [46] considered a mobile IoT network and proposed a method of selecting a relay based on the link reliability and the latency performance of the relay link. To capture the mobility of nodes in the network, a way-point mobility model was used. The relay selection problem was formulated as a joint minimization of the packet loss risk and the link latency parameters and solved after some reformulation. Using relay data sets, it was demonstrated that there was a linear dependence of the network latency on the node mobility variance. Furthermore, the proposed algorithm was shown to offer less overhead than two other routing protocols. The work assumed precise knowledge of the positions of the nodes. Different from the works in [46] and [77], where only data forwarding relay devices are selected, some works have proposed relay and source device selection algorithms. A case where source selection becomes necessary is where measurement of a parameter (such as soil moisture level, among others) is being reported by more than one IoT source device. In such applications, there must be a way to schedule which IoT device should report its measurement to ensure fairness. Zhang *et al.* [72] proposed a method to select source devices and relays in a manner that optimizes a defined fairness index and the end-to-end data rate for an AF relay-assisted IoT network. It is shown that the proposed schemes offer improved fairness performance when compared to an outage probability-only-based selection algorithm. The approach requires the acquisition of the CSI between nodes in the IoT network. Methods to select the source device are also proposed for an IoT network having an untrusted AF relay in Chen *et al.* [78] without relay selection. It was shown that the so-called optimal scheduling scheme offers improved secrecy throughput and secrecy outage probability over random scheduling and threshold scheduling techniques.

Redundancy from repeated transmissions from IoT end devices can improve reception quality at a relay, although there must be trade-offs between improved reception quality and the energy consumed by the relay node. This problem is addressed in [79], where a Euclidean distance-based similarity test is used to measure the redundancy between the received signals at the relay and to determine the wake-up time of relays in LoRa-based IoT networks.

The increasing miniaturization of storage chips indicates that storage capabilities can be integrated into sensors. This allows the integration of buffers into relays. Having buffers in relays allows packets to be temporarily stored for future transmission. When relays are equipped with buffers, there are more degrees of freedom in choosing a relay because not only is the link quality used for relay selection but also the buffer state can be used as a metric to select appropriate relays. Cross-layer relay selection algorithms with a buffer state-dependent metric are studied in [73]–[75].

The performance of a nonorthogonal multiple access (NOMA)-enabled IoT network with relays equipped with buffers is presented in [73]. In this work, six relay transmission modes are considered, including a NOMA mode. The proposed selection scheme selects a DF relay to transmit if its buffer state meets a system capacity threshold condition. The scheme is shown to offer improved throughput over orthogonal multiple access (OMA) and max-min selection approaches. However, the selection scheme in [73] requires global knowledge of the CSI. Having buffers in relays can also allow the use of one relay or a set of relays for the reception of information from the source and the use of another relay or set of relays for forwarding of the signals to the destination [74]. In [73], relays are assumed to have the same buffer size, although in practical applications, this may not be the case [74]. Such an asymmetric buffer size approach is considered in [74], where a relay selection method based on buffer occupancy and the data rate of the S-R and R-D links are used as metrics for selecting half-duplex relays. Considering relays with more than one antenna, the work linked each buffer space to a specific antenna and showed through simulation that the proposed approach achieved gains in reduced outage probability as the number of buffer spaces and relays increased. Both research contributions, that is, the contributions in [73] and [74], use half-duplex DF relays and assume that the relay has a sufficient energy supply to power its transmissions. Xia *et al.* [75] instead considered a single relay equipped with a buffer and proposed a transmission mode selection technique that chooses either to receive from the source IoT device or to transmit to the destination device. The selection metric used is the state of the relay buffers and the CSI of the relay link. Outage probability analysis in [75] showed improved performance over conventional opportunistic selection. The works [73]–[75] use outage probability as one of their performance metrics and employed a DF relaying protocol.

Key Insights: Cross-layer approaches to relay selection for IoT networks have mostly used relay buffer states, fairness

index and link latency as upper layer metrics in addition to a physical layer metric. When compared to noncross-layer approaches, the performance improvement of cross-layer relay selection techniques is most visible when the parameters of assessment are upper layer performance metrics, for example, data latency [46] and fairness [72]. Buffered relays that can opt to receive from IoT source devices or forward received signals to gateways are promising because the limited transmit and receive windows of IoT devices (which can be reconfigured as relays) do not need to be severely altered to be employed as relays.

C. INCENTIVE-BASED RELAY-ENABLED IoT NETWORKS

User-owned relay-capable devices (such as cars in vehicle-based IoT networks and drones) can, in theory, serve as relays in IoT networks. However, practically, owners of these devices may be uncooperative because of their self-focused nature. Where the reliability of an IoT network depends on an uncooperative relay, there is a high probability of network outages. In the works discussed in subsections III-A and -B, a general assumption is that relays are cooperative. This assumption may not hold when the devices are third-party owned, so appropriate incentives are necessary to motivate relay participation. In this subsection, incentive mechanisms proposed to motivate relaying in IoT networks are reviewed.

The works in [80], [82]–[84] proposed ways to motivate relay participation. Table 7 summarizes the approaches used by these works.

TABLE 7. Summary of incentive approaches in relay enabled IoT networks.

Article	Incentive	Approach
[82]	Optimized relay defined utility	Stackelberg-game
[80]	Bandwidth allocation	Vickrey auction mechanism
[83]	Transferable tokens	Blockchain smart contracts
[84]	low-power channel allocation	Analysis
[85]	Transferable credits	Nash Bargaining

The research in [82] and [80] considered relay-assisted IoT networks where a direct link between the source IoT device and destination IoT device exists to enable cooperative communication. Zhang *et al.* [82] considered a setup in which a relay-enabled IoT network is at risk of an eavesdropping attack. To motivate relay participation, a Stackelberg game is designed that allows relays and source IoT devices to define their utilities. Since relays exhaust their energy to forward messages for IoT source devices, the game seeks to improve the price of transmit power that the relay uses for data forwarding. Similarly, source IoT devices seek to improve the amount of power purchased from the relays. The simulation results showed that the proposed incentive

mechanism motivated relays to compete for improved utility. Furthermore, when the number of relays in the network is increased, the unit power price is reduced, giving IoT source devices a selection opportunity. To solve the problem of motivating energy harvesting access points (EAPs) to help charge sensors that report observations to a data access point (DAP), the work in [86] also proposed a Stackelberg-based incentive mechanism. A Stackelberg game was used to model the interaction between DAPs and EAPs and to capture the information asymmetry due to the DAP not knowing the channel conditions of the EAPs. The problem of incentive design was reformulated as a contract between the two entities. Through simulations, it was demonstrated in [86] that the effect of not having complete CSI at the DAP can be mitigated using contract theory. In effect, [86] extended the Stackelberg game for incentive design [82] in IoT networks to capture the case of information asymmetry.

Cooperative cognitive relaying is the approach put forward in [80] for an energy harvesting IoT network. In this work, secondary users (SUs) act as AF relays to forward data for a primary user (PU) pair and are rewarded by using the PU spectrum for SU communication. The work also proposed a Vickrey auction incentive mechanism to motivate SUs to relay the data of an SU pair in which the source SU is the auctioneer and the relays are the bidders. As in [82], the work in [80] shows that having more relays reduces the bid price and consequently decreases the utility of the relays. Similarly, when auctioneers require higher utility, the payment the relay enjoys increases. The Vickrey auction mechanism enforces positive utility. The incentive mechanism proposed in [80] is distributed, whereas for the work in [82], knowledge of associated channels (except the wiretap channel) is necessary and may require a central controller.

To reward multihop relay nodes in an IoT network, [84] proposed low-power channel allocation to the relays to compensate for their energy expenditure in forwarding signals for an IoT S-D pair in a linear network. The allocation is done in a manner that ensures equal energy expenditure in all the relay nodes. The approach offered reduced energy consumption compared to a random channel assignment method. It is not clear if the approach increases relay participation. A routing protocol for a multirelay IoT network is proposed in [83]. It exploits the public ledger property of blockchain to design smart contracts for relay requests and relay request acceptance. The proposed protocol was shown to demonstrate less overhead relative to the ad hoc on-demand distance vector (AODV) protocol. The proposed protocol uses multihop relaying. To motivate relaying among neighboring nodes, tokens are transferred to relays as earnings for providing forwarding service. Incentive design to motivate relay participation in a mobile crowdsensing system is studied in [85], where a data collector selects an intermediary device to forward sensed data to a requestor in a manner that improves the reward of the collector. The problem is modeled as a two-person cooperative game and solved using Nash equilibrium.

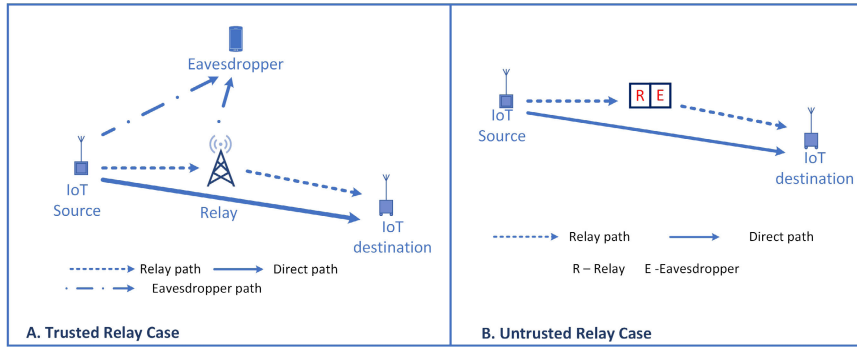


FIGURE 7. IoT relaying in the presence of an eavesdropper.

Key Insights: Incentive mechanisms proposed to motivate the participation of relays in IoT networks can be broadly categorized into 1) game theory-based incentive mechanisms such as the Stackelberg game [82], [86] and Nash bargaining [85], 2) auction-based mechanisms [80] and 3) token-based mechanisms [83], [84]. These mechanisms are also either deployed centrally with global knowledge of CSI assumed, or they are distributed, in which case a central entity is assumed to be nonexistent.

D. SECURE RELAY-ENABLED IoT NETWORKS

The presence of relays in the IoT network presents both an opportunity and a risk. Appropriately exploiting the resources of relays can offer improvement in the lifetime of the network and increase the reliability of the network. However, user-owned or third-party relays can be a source of a security breach in a case where malicious attacks are launched by such relays. This can compromise the information to be forwarded or, in a worst-case scenario, compromise the entire IoT network.

Registering and authenticating prospective relays can help streamline the number of acceptable relays by providing an identification method for these relays. Security measures become necessary when the presence of relays in IoT networks is opportunistic and their entry into and exit from the network is random. Table 8 gives a summary of the approaches used in the literature that focus on secure relay-enabled IoT networks. In this subsection, a review of recent research contributions to secure relay-enabled IoT networks is conducted with an emphasis on physical layer security approaches proposed and studied to date.

Physical layer (PHY) security has gained attention due to its unique features, such as eliminating the need to use encryption and the exchange of keys between large-scale IoT devices. With the increased computational capacity of devices, the use of cryptography is not completely foolproof, as eavesdroppers can acquire high capacity devices to break encryption. Hence, physical layer security continues to gain traction [87]. Through cooperative communication, relays can provide PHY security in the presence of eavesdroppers by increasing the secrecy capacity of the S-R-D link.

TABLE 8. Summary of secure relay-enabled IoT networks.

Article	Objective	Source of security risk	Approach
[91]	Minimize SOP, Maximize ergodic secrecy throughput	Untrusted relay	Signal jamming
[96]	Maximize secrecy capacity	Eavesdropper	Cooperative jamming
[88]	Sum-rate maximization	Eavesdroppers	Artificial noise, MIMO
[81]	Minimize SOP	Untrusted relays	Source selection and Optimal transmission time
[92]	Minimize SOP	Untrusted relay	Transmit antenna selection and relay selection
[89]	SOP optimization	Eavesdropper	Beamforming and Codeword rate optimization

However, in scenarios where the relay is untrusted, as in the case of third-party relay infrastructure or user-owned relays, the security risk increases. Secure relay-assisted IoT communication can be viewed from two broad perspectives, namely, the case of a trusted relay in the IoT network whose communication can be compromised by an eavesdropper and (2) the case of an untrusted relay whose forwarding services are required in IoT networks, as shown in Fig 7.

1) SECURE RELAY-ENABLED IoT NETWORKS WITH TRUSTED RELAYS

The use of artificial noise is proposed in [88] for an IoT setup that is at risk of an eavesdropping attack. In this work, a multi-antenna EH relay uses beamforming and artificial noise to improve the secrecy performance of the IoT network. Two cases of eavesdropper configurations are considered: a passive case where the IoT transmitter does not have the CSI of the eavesdropper's link and an active case in which the eavesdropper's CSI is available at the transmitter. Proposed solutions to the secrecy sum-rate optimization problems achieved a higher rate, which improved with an increased number of antennas at the relay.

The availability of location information and the CSI of eavesdroppers is an assumption made in some research work

in secure relay-enabled IoT. Acquiring such information is difficult and can contribute to overhead. Hence, [89] investigated the secrecy outage probability (SOP) performance of an AF relay-enabled IoT network exposed to eavesdroppers with an uncertain location. The work used the Poisson point process (PPP) to model the random locations of the eavesdroppers and showed through simulations optimal codeword rates and power allocation to improve the SOP of the studied setup. Cases of single and multiantennas at relays and eavesdroppers were studied. The relays used a randomize-and-forward protocol. The SOP of a trusted relay-assisted IoT network is also considered in [90]. The use of relays with hybrid AF and DF capabilities is studied in [90] to provide physical layer security in an IoT network at the risk of a single eavesdroppers attack. The relay with a link that offers maximum secrecy capacity is selected to forward signals to a destination. Closed-form expressions for SOP are derived and verified through simulations.

2) SECURE RELAY-ENABLED IoT NETWORKS WITH UNTRUSTED RELAYS

At the physical layer, the use of jammers can be employed as in [91], which presents an analysis of an AF relay-aided IoT network having an untrusted relay. To prevent the relay from decoding the signal it is forwarding, the relay's reception is jammed by a dedicated jammer device. At the destination IoT device, the relayed signal and the direct signal (from the IoT source device) are combined to improve reception quality. The performance of the proposed scheme showed improved SOP for various detection schemes at the destination node. Specifically, maximum likelihood and minimum mean squared error estimators at the receiver showed similar BER, SOP and ergodic secrecy throughput performance over the considered range of SNR.

Where potential relay nodes in the vicinity of an IoT source are not network registered and thus pose a risk of eavesdropping, (i.e., the relays are untrusted), employing the link quality difference between the S-D link and the S-R link can reduce the SOP of the IoT network [81].

In [81], the work considered a setup having a cluster of IoT source devices and a group of relay devices that harvest energy from surrounding radio frequency signals. The relays that are AF devices are considered to be eavesdroppers, so the target of the research is to select the source devices and the relays in a manner that minimizes the SOP of the setup. Hence, the authors propose a strategy that selects the source node and the relay node for which the source-destination (controller) link and the R-D link have the highest measured quality. Through simulations, they demonstrate that an energy harvesting duration exists within which an optimal SOP can be achieved. The proposed approach assumes that all the sensors within the cluster have the same information to send or that the priority of the sensors' data is link quality independent.

The works in [81], [91] and [92] studied networks with untrusted relays. Whereas jamming with artificial noise is

used in [91], the work in [81] used source and relay selection to improve the secrecy of relayed information. Similarly, in both works, relays were modeled to be AF relays instead of DF relays. Doing so prevents decoding of relayed information, although the relaying mode may be out of control of the IoT network operator for cases of third-party owned relays. However, the research contribution [92] proposed joint transmit antenna selection and link quality-based relay selection algorithms to improve the downlink SOP of an IoT network. The network was modeled as having a multiantenna base station and EH AF relays. The SOP and throughput performance showed improvement using the proposed selection algorithm.

Key Insights: In secure relay-based IoT network research, there has been more research contribution toward ensuring that an untrusted relay does not successfully eavesdrop on the communication of the IoT device pair [81], [91] and [92]. These works generally assume that the relay will use the AF protocol and consequently not be able to decode the relayed information-bearing signal. The features of blockchain technology make it an attractive tool for relay-assisted IoT communication. The diversity of operators of IoT applications poses data security and privacy issues for which the immutability and transparency features of blockchain can be an asset [93]. Running blockchain algorithms on UAVs (acting as relays for ground IoT devices) may be computationally demanding considering the power limitations of UAVs. Blockchain algorithms can be run on mobile edge computing (MEC) servers that receive measured acquired data from IoT devices via a UAV relay [94]. The work in [95] proposed storing the interactions between D2D devices and potential relays in blocks within the devices and showed through simulations that the proposed block-chain-based relay selection technique can result in higher utility. However, the computational time of their solution was not compared with other benchmark works.

E. IoT RELAYING BASED ON MOBILE NODES: UAV RELAY-ASSISTED IoT NETWORKS

UAVs are flying devices that have been shown to be capable of coverage extension and relaying the data of fixed ground sensors that are cut off from the network due to emergent situations such as a natural disaster. When obstruction occurs between IoT transmitters and their destination, UAV relays can fly to the transmitters to collect the data and fly to the destination to deliver the acquired data. UAVs are a typical example of mobile relays, and unlike mobile devices or vehicle-mounted relays, their elevation can be dynamically increased to achieve line-of-sight communication with ground devices. UAVs can help energy-constrained IoT ground nodes reduce transmit energy consumption as well. In [97], a framework for analyzing the performance of a D2D communication setup assisted by a UAV relay is presented. Specifically, the work derived expressions for the system sum rate and coverage probability and showed through simulations the optimal UAV height for optimizing these performance metrics. Furthermore, it showed the

dependency of the number of UAV stop points on the density of device pairs.

Ma *et al.* [98] demonstrated through a developed prototype that a relay mounted on a drone can improve the read range of RFID tags by approximately 10 times the case where a relay is nonpresent. Their results also showed that the relay was also able to offer a reduced localization error of approximately 19 cm. To achieve these results, the authors designed an RFID relay on a single printed circuit board that served as a transparent intermediary device between an RFID tag and an RFID reader. The drone flies on a predetermined path; hence, path planning was not part of the research. This onboard full-duplex relay uses baseband filters to exploit the guard band between uplink and downlink transmissions to overcome interlink self-interference at the filter. Furthermore, it uses an out-of-band full-duplex communication. For hardware, the relay is a custom-made PCB, and the drone is a Parrot Bebop2 drone. Although the work proposes methods for maintaining the phase of the uplink and downlink signals, it assumes that the drone-mounted relay is stationary in the air while receiving backscatter signals from the RFIDs, so the effect of drone speed on the range performance is not considered. The path of the UAVs is also assumed to be already optimally planned.

Different from the work presented in [98], in [99], optimal deployment of UAVs for mobile ground IoT nodes is performed with the aim of collecting ground data in an energy-efficient manner. To cater to the time-varying nature of the network resulting from the mobility of ground IoT devices, clusters of devices are created and dynamically updated. To ensure reliability in the mobile IoT network, discrete transport theory was used to model the interaction between mobile ground IoT nodes and UAVs. The resulting optimization problem was solved using the revised simplex method. The results showed that the ground IoT devices spent 56% less transmit power for uplink communication than the case where UAVs are fixed. Although both [99] and [98] considered UAVs collecting data from IoT nodes, [98] focused on range improvement and localization accuracy, whereas [99] focused on energy-efficient uplink transmission and optimizing the UAV flight path.

Motlagh *et al.* [100] presented two algorithms for solving the problem of selecting UAV relays that ferry observations between sensors and a BS. They formulated UAV energy consumption minimization and maximum transmission time minimization problems. For these problems, energy-aware and delay-aware algorithms were proposed. The results showed that having more UAVs to select from reduced the consumed energy of the network and the operational time when the target objective functions are energy efficiency and operational time, respectively. Similar to [100], the work by Chen *et al.* [101] also considered multiple UAV relays, although without UAV relay selection. The work instead compared the performance of UAVs forming a single multihop link versus UAVs forming various dual-hop multilinks. It first derived the optimal positions of the UAVs and showed

that the DF relaying protocol results in improved BER and probability of outage for both multihop and dual-hop relaying. The results also demonstrated that the multihop single UAV relaying case ensures better BER performance when the distance between source and destination IoT pairs is larger than for short distances.

Kong *et al.* [102] proposed a method for UAV relays to determine the optimal relay position that maximizes the link quality to solve the disconnectivity problem in a mmWave network. In the proposed approach, the UAV samples the channel states at few locations and uses 3D matrix completion to estimate the rest of the channel state along its flight path. This compressive sensing approach was shown through simulation to achieve higher accuracy but incur more time costs than the K-nearest neighbor and tensor recovery algorithms.

In [103], a rate maximization problem is formulated to optimize the UAV position, transmit power and allocated bandwidth. Considering a single UAV, a polyblock algorithm was proposed for reformulated subproblems of the original problem. The rate throughput performance of the proposed algorithm outperforms an equal power allocation-based UAV placement method. The problem of UAV relay placement is also studied in [104], where a method is proposed to fly a UAV relay to an optimal position without having global knowledge of the possible ground nodes for which it is relaying. In the proposed method, the signal strength and the angle of arrival of the signal between the ground units and the UAV relay are used to determine the optimal position of the UAV. Both mobile and stationary ground units were considered. Apart from theoretical analysis, the work used a quadrotor, and for ground units, laptops were used to demonstrate the effectiveness of their proposed method, which allows the quadrotor to move from a given initial position to the centroid of the ground units.

Time-constrained or delay-limited data need to reach distantly located controllers before these collected data become stale or outdated. There are IoT applications such as public safety focused, intelligent transportation focused and mission-critical applications that require timely report of sensor measurements. For such applications, the currency or timeliness of updates from sensors is key to achieving a correct response and facilitating decision making. In [105], the age of information (AoI) for an IoT pair is characterized as a metric for performance analysis of a UAV relay-assisted IoT network. In this paper, an AoI minimization problem is formulated that jointly optimizes the UAV trajectory and the allocation of energy (for the sender IoT and UAV relay). To solve the AoI minimization problem, the paper proposed iterative UAV trajectory optimization, energy allocation and packet service time optimization. The proposed solution results in a lower average peak AoI compared to a direct trajectory between the IoT pairs. The authors in [106] maximized the total IoT devices that a UAV relay serves by optimizing the UAV trajectory, bandwidth and transmit power allocation. To allow for the limited storage capacity of IoT ground nodes, the UAV is a full-duplex relay and is

TABLE 9. Summary of key contributions in UAV-based IoT relaying.

Contribution	Optimization Parameter					Performance Metric								Wing Type	
	BW	POS	PTH	RS	PWR	AoI	RG	DL	EE	S/L R	OP/BER	CP	N_u	RW	FW
[97]										✓		✓		✓	
[98]							✓							✓	
[99]			✓						✓					✓	
[100]				✓				✓	✓					✓	
[101]		✓									✓			✓	
[102]		✓								✓				✓	
[103]	✓				✓					✓				✓	
[104]		✓								✓				✓	
[105]			✓		✓	✓								✓	
[106]	✓		✓		✓							✓		✓	
[107]	✓		✓									✓		✓	
[108]			✓						✓			✓		✓	
[110]									✓	✓				✓	
[111]			✓		✓				✓					✓	
[112]											✓			✓	

cache-enabled. For the formulated problem, an iterative solution was proposed and showed an increased number of served IoT devices as the cache size of the UAV relay was increased. Similarly, Samir *et al.* [107] maximized the number of served IoT devices by jointly optimizing the UAV trajectory and the radio resource allocation for a UAV-assisted IoT communication setup. To solve the mixed-integer nonconvex problem, the authors employed successive convex approximations to achieve suboptimal solutions. For the special case where the take-off and landing locations of the UAV are known, a distance minimization algorithm was proposed. To address the case where sensed data do not have uniform deadlines, Ghdiri *et al.* [108] investigated using multiple UAVs to serve clusters of IoT devices. Specifically, the work in [108] focused on optimizing the number of required UAVs, UAV trajectories and cluster formation to minimize the total energy consumed for data collection. To cluster the IoT sensors, the authors proposed an improved K-means algorithm, and for cluster head positioning, the algorithm minimized the distance between the UAV dockstation and the cluster head. The authors modeled the multi-UAV trajectory optimization problem as a directed graph and showed that tabu search obtained the preferred multi-UAV trajectory design. The problem of UAV relaying for data collection in IoT networks becomes more tasking when the ground nodes are mobile [109].

Three optimization problems are the focus of the work in [110], where practical considerations such as sparse distribution of IoT sensors and the limited transmission range of a full-duplex-rotary-wing UAV are made. Specifically, the work sought to maximize the system sum throughput and minimize both the total energy consumed and the total time required for end-to-end communication. Secrecy communication is considered in [111], wherein a UAV not only serves as a relay to the ground node but also acts as a jammer. Specifically, the full-duplex UAV uses jamming signals to limit a potential eavesdropper from intercepting confidential information from the IoT ground node. The authors aim to maximize the energy efficiency of UAV-assisted secrecy communication by optimizing the UAV trajectory and the transmit powers of the ground units and of the UAV. Using an iterative approach to solve the formulated maximization

problem, the authors showed that improvements to the energy efficiency can be achieved. Ji *et al.* [112] derived the outage probability and BER expressions for a UAV relay-assisted IoT network with energy harvesting at the UAV relay for Nakagami-m-affected channels. In studying the performance of the setup, both TS and PS energy harvesting protocols were considered, and simulations were used to verify the derived expressions.

F. RELAY PHYSICAL INTERFACE DESIGN

As there is a growing body of work focused on theoretical analysis and algorithm designs for relay-assisted IoT networks, there are also research contributions that have studied the practical deployment of IoT relays. Flauzac *et al.* [113] considered the practical use of a modified LoRa node as a relay to extend the coverage of a LoRa gateway to an isolated IoT node. They proposed the use of LoRa between the IoT end device and the relay and the use of the LoRAWAN protocol to send the data from the relay to a gateway. The relays first joined network gateways through join requests before being attached to IoT end nodes through synchronization signals and data request messages. The network considered in [113] is a linear network that is application-specific. Similar to the work in [113], a two-hop relay is also considered an addition to a LoRa-based IoT network after network deployment in [8]. Although similar to end devices in hardware, the relay does not perform sensing and aggregation (unlike the relay in [113]). Furthermore, asymmetric synchronization between the relay and IoT end devices is proposed without a real-time clock to guarantee time synchronization. Unlike the works in [8] and [114], where modified IoT end devices were used as relays in practical relay enabled IoT networks, in [31], a prototype of a mobile phone relay was presented. In so doing, no modification is needed on the relay's physical features. The work in [31] used a smartphone to forward medical data from a sensor to a central server without the use of a gateway. BLE is used as the connectivity technology between the sensor and the smartphone that accesses the central server using an IP network. In this work, time synchronization between the sensor and smartphone relay is not considered since the smartphone does not require wake-up and sleep

TABLE 10. Practical relay hardware design.

	[113]	[8]	[114]	[31]	[116]
Hardware	Not clear	Arduino ProMini	Waspnote Pro	Samsung Galaxy Note 8	EFM32GG-STK3700 Giant Gecko and iC880A concentrator board + a Raspberry Pi 3
μC	Not clear	ATMega328P	ATMega1281 Snapdragon 835	Exynos 8895/	EFM32GG990F1024
Synchronization	Symmetric	Asymmetric	Symmetric	Symmetric	Symmetric
Processing	None	None	None	None	None
Connectivity Technology	LoRa	LoRa	LoRa	BLE	LoRa

times but rather needs to have a health app installed. The hardware of the end device (an EFM32GG-STK3700 Giant Gecko [115]) and a gateway (iC880A concentrator board and a Raspberry Pi 3) are combined to create a forwarder node in [116] for a LoRaWAN-based IoT network. To minimize packet collision, the wait time of the end device was increased to give the relay some wait time to obtain a reply from the gateway before sending it on the downlink to the end device. The testbed was shown to reduce packet loss in comparison to a bad direct link. Table 10 summarizes the contributions regarding the aspect of relay physical interface design.

Key Insights: From the surveyed literature, practical relays for IoT networks can be modified IoT end devices [8], [114]. In actual relay deployment, relays can be strictly receive-and-forward devices. That is, no further processing is carried out on the relayed signal [8], [113], [114]. Although there is extensive research work on EH relaying, in actual relay deployments, the relays have residual energy sources [8], [114]. The hardware combination of the end device and gateway can be used as a relay [116]. Software modifications can be made to IoT end devices and gateway hardware to make them act as relays [116]. Furthermore, from the reviewed literature, a testbed for relaying in an IoT network that uses NB-IoT as a connectivity technology has not been studied.

G. BROADER PERSPECTIVES ON RELAYING IN IoT

Apart from the approaches to relaying challenges in the IoT that have been discussed in subsection III-A-E, allocating radio frequency resources to relay transmission has also been considered in a few studies [77], [117]. The low computational capacity of IoT devices would greatly favor a centralized resource allocation undertaken by a gateway or a BS. A distributed approach to resource allocation would require lean algorithms and some knowledge of the link information of the associated channels. Full-duplex relaying has also been studied for the IoT, an attraction being the reduced number of time slots it requires in comparison to half-duplex communication [118]. There are other research areas (such as NOMA and edge caching) that are gaining increasing attention in relation to relay-assisted IoT networks. In this subsection, other perspectives on relaying in the IoT are discussed.

1) RADIO RESOURCE ALLOCATION IN RELAY-ENABLED IoT

A closed-form expression for the energy efficiency of a relay enabled massive IoT network is derived in [117], where a DF

relay equipped with multiple antennas helps forward the data of a large number of IoT device pairs. The aim of the work in [117] is to allocate relay transmit power, the number of relay antennas and the number of IoT device pairs in a manner that optimizes the derived energy efficiency of the network. For the formulated problem, a resource allocation strategy to minimize the lower bound of the energy efficiency was shown through simulation to be less computationally demanding than the exhaustive search algorithm, although with a reduced energy efficiency penalty.

Mobile relay-assisted IoT networks or relay-assisted mobile IoT devices have a dynamic topology due to the mobility of the relay nodes or IoT nodes, respectively. To perform relay selection or channel assignment for such a dynamic setup may require CSI that is being updated often. Acquiring updated CSI within short intervals can lead to signaling overhead due to the number of training symbols or the channel feedback resulting from the constantly varying topology. To combat this challenge, resource block assignment based on the Chinese Remainder Theorem (CRT) is proposed for cellular network-provided relay-assisted IoT networks [77]. The assignment does not require the availability of CSI and central coordination from the BS because the relay terminals generate the sequence for resource block assignment in a distributed manner. The approach was shown to reduce the probability of neighboring relays assigning the same RBs, which can deteriorate the performance of the IoT network. The approach requires a level of coordination between relays and the IoT devices, and the rigor of sequence generation may not suit the energy bounds of mobile devices.

Although both [117] and [77] consider resource allocation, the work in [117] does not focus on resource block allocation but rather on allocating a number of relay antennas and relay transmit power. Both works considered cellular networks to provide IoT networks with fixed relays in [117] and mobile relays in [77]. Tefek and Lim [119] proposed two relaying techniques to enable massive access of machine-type communication (MTC) devices. In the first technique, which is signal-to-interference (SIR) relaying, DF relays only forward the signals of devices with strong SIRs, whereas in the location-based technique, the signals of MTC devices closest to the relays are forwarded to the base station. The density of the MTC devices was shown to determine the comparative outage probability and the transmission capacity performance of the relaying schemes. The work also demonstrated that there exists an optimal frequency resource

partitioning between the devices to the relay link and the relay to the BS link.

2) FULL-DUPLEX RELAY-ENABLED IoT

Half-duplex relaying is popular in relay network research. However, with recorded success in self-interference cancellation (SIC) [120], interest in full-duplex relays is increasing. In [118], full-duplex multihop DF relaying is analyzed with each successive relay node experiencing self-interference, relay interference and interference from neighboring active nodes. Different from other full-duplex relaying works, the Markov chain model is used to model the end-to-end error probability of the IoT setup. Through analysis and simulations, it was demonstrated that the choice of FD over HD relaying depends on the level of self-interference that the network can accommodate and where there is cluttering from randomly placed interferers. Short-distance multihop communication is preferred, although the availability of CSI is assumed, and the relays despite being randomly positioned are static. The work in [121] studied the outage probability and network capacity performance of a cellular-based massive machine-type communication (MTC) assisted by in-band full-duplex (IBFD) relays. The network capacity of the IBFD relay-based network did not outperform an HD-based system when the considered nodes were modeled as homogeneously and independently distributed Poisson point processes (PPPs).

3) EDGE CACHING-ASSISTED RELAYS IN THE IoT

The advantage of equipping relays with memory capability to enable the offer of additional services beyond signal forwarding has been highlighted [122]. Fixed relays are mostly placed at the edge of the network to ensure proximity to the end users. Such proximity provides the opportunity to reduce the load on the core network by prefetching popularly requested user content to relays from the core network during off-peak periods. This relevance of edge caching becomes more glaring when ultrareliable and ultralow latency applications are considered. In IoT networks, the performance of cache-assisted relaying has been studied for static relays [123], [124] and mobile relays [125]–[128], and common performance metrics have included outage probability and error rate.

The effect of increasing the computational task of a network can be reduced when a relay is cache-enabled. This is shown in [129], wherein a cache-enabled relay assists source devices in offloading computational tasks to destinations. With cache-enabled relays, source devices are less likely to be in outages, and latency is reduced in comparison to cache-free cases. The work in [123] considered cache-enabled infrastructure FD relays that provide popular multimedia content to users within its coverage. In the network considered in [123], caching is also performed at the user levels where devices can fetch cached content from nearby users through D2D communication. Such a setup has potential for smart city IoT networks, where devices can keep contents downloaded

from a cache relay. The user devices can offer their downloaded content on request through. To reap the benefits of caching, the density of cache-enabled relays needs to be high in response to high user density. However, where the density of the relays cannot meet the download request of massively deployed users, the BS can compensate for the shortfall through the relays [123]. For aerial relays in IoT networks, cache-enabled UAVs can wait a predetermined time before flying toward the destination. In so doing, the energy efficiency of the network can be improved when combined with an appropriate trajectory optimization strategy [127]. Cache-enabled aerial relays are studied by Jiang *et al.* [126], who optimized the 3D location of UAVs and the optimized file caching location to obtain improved data throughput.

Equipping relays with caches implies that where a user requests a file that is among the files cached at the relay, dual-hop communication is reduced to a single hop, assuming no D2D communication. It also implies that the interference experienced by the two-hop communication is reduced. In particular, the destination alone becomes the interference target [124]. Such a scenario clearly plays out in [124], where cache-enabled relay-assisted networks demonstrate improved outage performance over relay-assisted networks without caching at the relay.

4) NOMA-ASSISTED RELAYING IN THE IoT

Orthogonal multiple access technologies have been used to provide access to users in cellular networks. The emergence of IoT networks that will be characterized by ultra-dense deployment stretches these orthogonal technologies to their resource limits. Recently, nonorthogonal multiple access (NOMA) has received much research interest as an access technique that can permit densely deployed devices to use the same orthogonal time-frequency resource by exploiting the power and code domains [130], [131]. NOMA has been combined with various other technologies, specifically, cognitive radio [132], SWIPT [133], MIMO [134], D2D communication [16] and cooperative communications [16], [135], [136]. When combined with cooperative communication, the relay is mostly modeled as providing NOMA access to IoT devices [137]. In the literature, NOMA improves spectral efficiency, provides access to more users and improves the EE of considered networks.

In [138], uplink and downlink secure IoT communication based on NOMA is demonstrated. The achievable secrecy rate performance showed that the NOMA system, although it outperformed an OMA equivalent, suffered degradation in performance in a short packet scenario. In [133], derivations of the analytical expressions for outage probability and ergodic capacity of a bidirectional relay-assisted IoT setup are presented. The relay in the proposed model aids the communication between two groups of NOMA users and harvests energy from their communication. Considering hardware impairment of communication components, specifically the resulting in-phase and quadrature imbalance, X. Li *et al.* [139] showed that such impairment can limit

TABLE 11. Summary of existing contributions on machine learning for relay-based IoT networks.

Existing Contributions	Machine Learning Tools					Main Applications						
	FFN	DNN	RNN	DT/SVM	RL	RS	AS	PHS	CAR	AC	PA	
[60], [150], [154], [164]		✓				✓						
[151], [165]	✓					✓		✓				
[166]–[168]					✓	✓						
[152]					✓					✓		
[153]				✓		✓		✓				
[169]		✓									✓	
[157]				✓		✓		✓				
[159], [170]		✓				✓		✓				
[160]		✓		✓		✓		✓				
[163], [171]		✓					✓	✓				
[172]				✓		✓						
[173]			✓			✓						

the outage probability and ergodic capacity performance of NOMA-based relaying in IoT networks. NOMA-based relaying can also be susceptible to eavesdropping attacks when the eavesdropper has a better channel than the target receiver. To address such a challenge, transmission of artificial noise by a two-way full-duplex relay was proposed by Zheng *et al.* [140].

IV. MACHINE LEARNING AND AI FOR IoT RELAYING

Future generation communication networks are envisioned to support applications that have stringent quality of service (QoS) requirements, such as ultrareliable low latency communication. Next-generation networks are also expected to be dynamic owing to the diverse applications that will be supported. To meet these requirements, artificial intelligence and machine learning are key technologies that have been proposed. Massive Internet of Things devices generating large volumes of data will require the power of machine learning and intelligence to coordinate their activities. This intelligence will not be operational at the core network only but at the edge as well.

As a consequence of extreme requirements, next-generation wireless networks will feature unprecedented complexity, thereby limiting the applicability of classical mathematical model-based design methodologies for network design, deployment and network resource optimization [141]. Machine learning (ML) and artificial intelligence (AI) are therefore expected to play a pivotal role in the design of all aspects of wireless networks. This has led to a surge in the number of published works exploring ML/AI-based data-driven solutions for solving challenges associated with different aspects of wireless network design, including radio propagation [142]–[145], wireless signal identification [146], access control and routing protocols [147] and radio resource management [148], [149]. ML- and AI-enabled relaying in IoT networks has also received significant research attention. The focus has been on the application of various ML algorithms to solve different challenges associated with relaying in IoT networks.

We now present a review of selected existing work on ML for relaying in IoT networks. For clarity, we group these works according to the ML techniques used. For each technique, we provide a concise introduction to the method followed by a review of related papers. A summary of the existing works applying ML to relaying in the IoT is presented in Table 11.

A. SUPERVISED LEARNING

In supervised learning, an ML model is trained to approximate an arbitrary function using examples that are either collected from real measurements or generated synthetically. Depending on the type of output, supervised learning models can be classified into regression or classification models. While the latter is used in predicting the probability of a given input belonging to a particular class or classes, the former is used to approximate continuous functions. In designing supervised learning-based algorithms, there are multiple stages that can be grouped into training and execution phases. In the training phase, examples (sets of input and output values) are used to optimize the weights of the model using gradient descent algorithms. In the execution phase, the trained model is applied to perform predictions or to label new data.

Different supervised learning algorithms, including support vector machines (SVMs), feed forward neural networks (FNNs), deep neural networks (DNNs) and decision trees (DTs), have been used in existing studies considering relaying in IoT networks; see, e.g., [65], [150]–[163]. A key bottleneck in conventional relaying is the acquisition of accurate CSI. Conventional relaying based on mathematical optimization requires global CSI. However, with large-scale device deployment in future networks and real-time IoT applications, CSI acquisition can add to communication overhead and delays. Supervised learning combined with deep neural networks can offer real-time relay selection algorithms in IoT networks [150]. Considering the nonlinearity in EH relays, [150] developed a DNN-based model for relay selection by using throughput-dependent parameters such as SNR, number of users and relay position for offline

training. One-time offline model training, as in [150], results in lower complexity selection algorithms and can offer a real-time selection advantage; however, offline training still needs the resources of central entities such as access points or base stations. Neural network relay selection was shown to offer throughput performance improvement over an SVM approach in [164].

B. REINFORCEMENT LEARNING

As stated above, supervised learning methods require the availability and/or generation of labeled data sets to train a neural network. In many applications, it may be nearly impossible to obtain such data sets. This is particularly true for most problems associated with relaying in IoT networks due to the nonavailability of labeled data. Reinforcement learning (RL) ameliorates this problem by instead allowing neural networks (often referred to as agents) to learn through a *trial-and-error* procedure involving interactions with the environment. During this interaction, a carefully designed reward signal is used to guide the agent(s) toward learning to successfully perform a given task. For this reason, RL methods, including multiarm bandit, Q-learning and deep Q-RL, are becoming increasingly popular for many wireless communication applications. As seen in Table 11, research on RL for relay-enabled IoT is still limited; however, we foresee a surge in its application in the near future.

In [152], a low-complexity mechanism for relay scheduling in cooperative IoT networks using a stateless RL method - the multiarmed bandit (MAB) - is investigated. The authors utilized the MAB framework to learn relay scheduling using only the acknowledgments (and negative acknowledgments) of packet transmissions. Despite the limited information used for scheduling decisions, this method still shows comparable performance to optimal scheduling based on full-CSI but with lower complexity.

V. APPLICATIONS OF RELAY-ENABLED IoT

Relay-enabled IoT finds applications mostly when the transmitting node or sender in an IoT setup requires assistance in delivering its data to the gateway through which the network server can be accessed. In such cases, adjacent or neighboring nodes could be selected to deliver the data. Such adjacent nodes could be static or mobile. Additionally, the use of relays could be opportunistic in which an available node is selected based on some criteria, as discussed in subsection III-B, or it could be preplanned in which case the relays are included in the network rollout or deployment. In the reviewed research contributions for this paper, some research work focused on relay-aided IoT networks tied to specific applications. In this section, such works are reviewed to showcase the use cases for relaying in IoT networks.

A. MEDICAL MONITORING OR REMOTE HEALTHCARE

Sensors strapped to the body can report health indicators such as the blood pressure and sugar level to a remote server that is accessible to health care providers. Such reports can

be critical in offering timely diagnoses and providing interventions, especially for remotely located patients. In [174], a relay-assisted IoT setup was proposed for healthcare parameter monitoring for patients in rural areas. Simulations were used to analyze the end-to-end delay, throughput and energy consumption of the proposed setup. The work considered a case where a large array of sensors opportunistically transmits the information of a source to a relay that sends the same information to the network. This approach largely assumes a static relay and does not factor in the mobility of the source nodes or the relay. Sometimes the patients from whom health parameters are required may not be in the region of an access point and might need to utilize mobile devices as relays to forward data. Hence, mobile relaying is a key area for research in healthcare-oriented IoT.

Opportunistic relays can ensure connectivity for patients who require forwarding services. A relay-enabled IoT network using Bluetooth low energy (BLE) technology is implemented to forward medical data to an IoT server using third-party mobile relays in [31]. In the work [31], the mobile relay, which is selected based on the best-received signal strength (RSSI), establishes a secure connection to an IoT server and is rewarded after successful completion of the forwarding process. The testbed performance showed that the probability of meeting a mobile relay increased with the increase in the arrival rate of mobile relays into the network.

Another issue apart from mobility management in medical IoTs is the issue of maintaining the confidentiality of the transmitted information in the case of untrusted relay nodes. [31] proposed having the relay nodes register with a server through an application installed on the mobile device.

The abovementioned works under relaying in medical or healthcare IoT assume that the medical information to be relayed through a network for response is of equal priority. This could be so when a patient has only one sensor that sends unique priority information. Where there is multipriority information to be relayed, the scheduling needs to be a QoS-aware implementation. In [23], the authors proposed a QoS-aware relaying technique for a wireless body access network (WBAN). On-body sensors can also serve as relays in medical IoT in WBAN applications. These sensors can help forward the signals from body implants to a local collection point, such as the mobile device of the patient with a specialized medical monitoring app. This information can then be sent through the cellular network to medical personnel for a prompt response. Fig. 8 shows a set up for medical IoT.

B. SMART TRANSPORT

The IoT is envisioned to change the way people move around. This will be accomplished by adding a level of intelligence to the transport system in cities. The IoT is looked upon to help cities plan roads based on the data obtained from road-installed sensors and the data reported from sensor nodes installed in vehicles. Armed with such data, city transport agencies can plan better, and vehicle owners can also reserve parking spots in advance. Car owners can also avoid

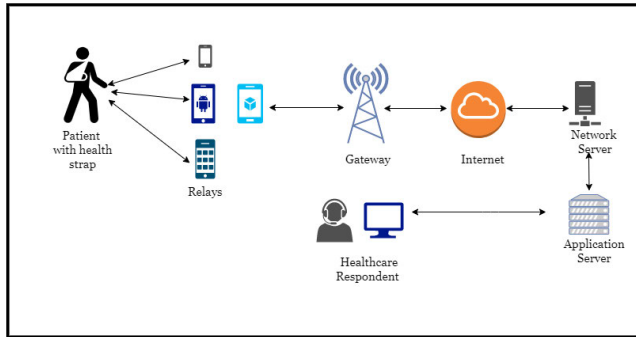


FIGURE 8. Relay-aided health monitoring IoT setup.

crowded routes for alternative less congested routes. The application of relay-aided IoT in transportation finds expressions where road-installed sensors can take advantage of the presence of relay nodes installed in vehicles to forward messages to a server. This application can take advantage of the available energy of the car that powers the sensor to forward data. Such an approach was studied in [175], where the use of vehicle-mounted relays to assist in forwarding delay-sensitive data between IoT devices and servers was considered. The authors demonstrate through simulation that having many vehicles participate in NB-IoT networks can reduce the message loss probability and increase the energy efficiency of IoT networks. As vehicles are mostly driven by humans (who are self-focused), an incentive mechanism to motivate relaying needs to be designed in the proposed framework. In [176], UAV-assisted vehicle-to-vehicle communication is modeled as a Markov decision process, and a total throughput maximization problem is formulated for the UAV-to-vehicle downlink. This paper proposed a deep reinforcement learning-based algorithm to allow the UAV to determine the optimal policy to optimize the total throughput. Specifically, the UAV learns its optimal 3-dimensional position and transmission control (i.e., bandwidth and power allocation).

C. POWER LINE COMMUNICATION

An intelligent electricity grid is a thriving research area wherein methods have been developed to make the network respond better to consumer-side demand. IoT-based power line communication (PLC) can enable smart grid communication. The research in [177] considered a hybrid power line and wireless sensor network assisted by relay nodes. In this work, closed-form expressions of the outage probability and BER of the setup were derived with accompanying performance analysis. Using simulations and numerical analysis, the gains of the proposed setup were shown. The relay strategy is DF, and although relay selection is not performed, relay interface selection between wireless and PLC is performed based on the acquired SNR. Unlike the work in [177], which considered the channels in the IoT setup to be experiencing Rayleigh fading, two distributions are used in [178], where the S-R and R-D channels follow a Nakagami-m and a log-normal distribution, respectively. The single relay considered

is a PLC and wireless hybrid AF relay assisting a source IoT device to forward its information. Analytical expressions are derived for the IoT setup for metrics including outage probability and BER, which are verified through simulations.

Similar to the work in [178], Chen *et al.* [179] analyzed a hybrid fading scenario having both a wireless and PLC interface for the S-R and R-D links, respectively. The wireless channel was modeled as a Nakagami-m fading channel, whereas the PLC channel was represented with a lognormal distribution for a single AF relay. The work analyzed the performance of the relay setup for a scenario where the channel gains of both S-R and R-D links are approximated to have gamma distributions and a scenario where both channels are approximated to have lognormal distributions. Similar to the work in [177] and [178], the work in [179] considered the presence of a single fixed relay.

D. ULTRARELIABLE LOW LATENCY COMMUNICATION (URLLC) APPLICATION

Relays are also useful in URLLC applications, which are delay-sensitive applications that involve the transmission of short packets. Although introducing relays into URLLC applications may slightly increase the delay in packet reception, relays can guarantee meeting reliability targets of such critical applications. It has been shown that for a finite blocklength scenario, which is characteristic of URLLC applications, two-hop relaying results in better reliability performance than direct communication [180]–[182].

Examples of such URLLC applications are factory automation [181], military operations, augmented reality, cyber-physical systems, and intelligent transport systems [183]. To meet the stringent performance requirements of URLLC, approaches have included optimizing the packet length for the application [184] and reducing the latency experienced by the considered system [183], [185].

The research in [184] proposed iterative algorithms to solve a UAV decoding error minimization problem for a front-line operation. The algorithm iteratively found the optimal packet blocklength for fixed UAV location and vice versa. It was shown that it matched the performance of an exhaustive search algorithm in error decoding probability, albeit with lower complexity. Traditionally, research in wireless relaying has assumed infinite packet blocklength transmission. However, for URLLC, there are stringent limits for packet sizes. Considering fixed packet sizes, the work in [183] proposed VLC communication between traffic infrastructure and vehicles via a DF vehicle relay. The analysis showed improved latency performance (sub-milliseconds) and packet error rate performance over an RF-based vehicle-to-vehicle (V2V) relaying system.

Pilots that are inserted into packets for channel estimation purposes can contribute to increased packet sizes, especially in delay-sensitive cases such as URLLC. However, pilot length optimization for URLLC involves reaching a compromise between reliability through good channel estimation and low delay using reduced pilot symbols if the delay introduced

by the relay is ignored [185]. Achieving the delay and reliability requirements of relay-based URLLC also requires a suitable relay selection technique. Dense deployment is common in URLLC applications, and consequently, selecting a set of good relays for short packet communication is important [186]. Whereas selection techniques that assume static channels within the coherence time can offer improvement in error rate, relay selection algorithms that are channel-dynamics-aware can offer an approximate 10% improvement in error rate [187]. Furthermore, when the duplex method is considered, URLLC applications fare better (in terms of block error rate performance) with full-duplex relays than with half-duplex relays [188].

VI. OPEN ISSUES

From the research contributions that have been surveyed, various investigations have been made into the feasibility of having relays in an IoT network. Some of the challenges of IoT relaying, such as relay selection, have received greater focus than others, such as relay mobility. These challenges and the approaches put forward in the literature stimulate open issues that can inspire future research directions. In this section, some of the open issues are discussed.

A. FEDERATED LEARNING IN RELAY-ENABLED IoT NETWORKS

The current approach to machine learning in relay-enabled IoT networks is centralized except for the work in [189], where relaying is offered to edge mobile devices as a service. Centralized machine learning raises the concern of user data privacy. Federated learning overcomes this hurdle by enabling the central server to send models to users who train these models based on their local data. Updates are then sent by the users to the global model. Federated learning assures user data privacy, as users only send model updates. In federated learning over wireless networks, selected edge devices that carry out local training may be in an outage state. In such a scenario, relays can assist in forwarding the model updates and ensure model accuracy and link reliability. Such a scenario results in joint optimization problems that include optimizing relay selection and model accuracy, among other parameters. These problems, often NP-hard and nonconvex, are likely to require problem decomposition and the use of heuristics. Relay-assisted federated learning for IoT networks is an exciting area that requires further investigation.

B. RELAY-ENABLED IoT NETWORK TESTBEDS

Although there is teeming literature on relay-enabled IoT networks, there has been much focus on the analytical and theoretical framework, whereas actual demonstration through hardware implementation has not kept pace with the theoretical analysis. A few works have demonstrated through testbeds [8], [31], [114] the various use cases of relay-enabled IoT. Testbeds can help show a proof of concept, especially in the area of EH relay-enabled IoT networks considering the energy constraint of IoT nodes. Hence, more research effort

needs to be employed in developing testbeds to determine whether the actual deployment of IoT relays matches the theoretical analysis.

C. MODELING MOBILITY OF MOBILE RELAYS

When relay nodes are not static devices but rather mobile devices, the connectivity they provide to source-destination nodes may be erratic due to the mobility of the relay nodes. This can be a problem if the source node being assisted is a patient's on-body sensor that reports urgent data through the relays. To capture the variations that such mobility brings to the network, [46] used time-varying network graphs, which would require frequent updating. Moreover, variations in device position can also be presented as uncertainty in CSI acquisition and added as an error term to the channel gain. For this, an uncertainty-aware relay power allocation algorithm can be used, except that for serious uncertainty cases, the energy store of the relay will be drained. Hence, mobility-aware relay-enabled IoT is an area of future research. An approach could be the use of ML algorithms that are trained by the mobility history of user-held devices.

D. OPTIMAL RELAY PLACEMENT

Some works have shown that with one or multiple relays, the reliability of an IoT network can be improved; for example, see [68]. However, optimal positioning of these relays has not been investigated. For a single relay, a straightforward approach would be to position the relay midway between the IoT end device and the gateway. However, when there are many IoT end devices, such as smart agriculture occupying a large geographical area, it remains to be shown whether midway positioning would be optimal. Such optimal placement can be a metric to select a mobile relay when it is in a defined optimal region.

E. LEAN CSI ACQUISITION TECHNIQUES

Traditional or conventional relaying relies on the availability of CSI to make relay selection decisions. The channels for which CSI acquisition is critical include the relay-to-destination channels. With massive deployment of devices, the number of devices from which a relay can be selected increases. For such many devices in a relay set, acquiring perfect CSI can potentially weigh heavily on the overhead. Moreover, for URLLC applications, where short packet communication is a key feature, perfect CSI acquisition can cause severe delays. Despite the gains of NOMA, as demonstrated in spectral efficiency and secrecy probability gains, NOMA requires knowledge of the existing channels. Therefore, an exciting area for research is efficient CSI acquisition in relay-enabled IoT networks. ML/AI-based relaying in the IoT has been shown to offer reduced complexity; specifically, complexity reduction can be achieved using deep neural networks. However, these approaches are largely centralized approaches that may be challenging due to the distributed nature of certain IoT applications.

VII. CONCLUSION

Due to obstructions and fading, the quality of the direct link between source and destination devices might require that a relay be coopted to help forward signals to the destination. The availability of relay nodes provides both opportunities and challenges. The gains of relaying indicate that relays can be built into the IoT architecture or that the presence of relays can be exploited opportunistically for data forwarding.

Resource constraints in relay nodes, specifically energy, can be relieved using energy harvested from radio frequency or from green energy sources, including solar energy. Harvesting energy and transmitting information concurrently, however attractive, comes with its hardware complexity constraint. Relay selection, a classic problem in relay networks, has a spectrum of algorithms put forward to offer near-optimal and optimal solutions. In this survey, the above aspects of relaying in the IoT were comprehensively reviewed. Topical classifications of current approaches employed in the literature have been discussed. Possible application areas of relay-enabled IoT have also been surveyed. Incentive-based approaches to relaying have also been examined, and the application areas of relay-aided IoT networks have been laid out. Open issues in relaying in the IoT have also been discussed.

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