Journal of Network and Computer Applications 97 (2017) 79–95

Contents lists available at ScienceDirect

Journal of Network and Computer Applications

journal homepage: www.elsevier.com/locate/jnca

Energy efficient device discovery for reliable communication in 5G-based IoT and BSNs using unmanned aerial vehicles

Vishal Sharma[a], Fei Song[b], Ilsun You[a,*], Mohammed Atiquzzaman[c]

[a] Department of Information Security Engineering, Soonchunhyang University, Asan-si 31538, Republic of Korea
[b] School of Electronic and Information Engineering, Beijing Ji aotong University, PR China
[c] School of Computer Science, University of Oklahoma, Norman, OK, United States

ARTICLE INFO

Keywords:
IoT
UAVs
Body sensor networks
5G
Energy

ABSTRACT

Connectivity among real-world entities is one of the primary requirements of the upcoming Fifth Generation Public Private Partnership (5G-PPP). Both Internet of Things (IoT) and Body Sensor Networks (BSNs) are major applications of 5G networks. However, over-consumption of energy for device discovery, which includes registration, removal, querying, routing etc, quickly depletes the resources of a node, which may further influence the whole network. There are a number of approaches which provide energy efficient mechanisms for the selection of devices in a network operating with different types of nodes; however, these approaches are unable to maintain a high transmission capacity along with energy conservation and fault-tolerance. In this paper, an energy efficient approach for device discovery in 5G-based IoT and BSNs using multiple Unmanned Aerial Vehicles (UAVs) is presented. A functional architecture is proposed, which utilizes XML charts to perform device discovery on the basis of networks state cost and available energy. The significant gains achieved in energy consumption, end to end delays and packet loss show that our solution is capable of providing energy efficient device discovery with 78.4% reduction in the overall energy consumption compared to existing solutions. The advantage of UAVs in energy efficient networking is illustrated using numerical analysis which suggests 75% enhancement in the energy-asymptote of the existing networks.

1. Introduction

With the ever increasing demand of the users to seek all the information on the go, Internet of Things (IoT) and Body Sensor Networks (BSNs) have evolved as two of the promising areas of research. IoT aims at connecting all the devices on the network to provide a common platform for information sharing. It is predicted that the number of devices for IoT and BSNs will be more than 50 billion by 2020 (Higginbotham, 2011). This is a huge number and will certainly require efficient network approach for handling so many devices.

BSNs comprise multiple sensors which can be installed as on-body or out-body devices which can support the efficient management of the organs to maintain a healthy life. A simple chip implanted on a body can send regular updates to your smart devices or even to a nearby hospital in the case of emergency by connecting body sensors to the network as a part of IoT. Thus, BSNs can be considered as an integral part of the IoT. BSNs have already been studied and implemented as a part of stand-alone applications using specially designed standard (IEEE 802.15.6) for transmission (Kwak et al., 2010). However, with the advent of IoT, it is necessary to include BSNs as body sensors are the crucial devices which are to be connected as a part of IoT.

With the advancement of the Fifth Generation Public Private Partnership (5G-PPP), these devices are considered as an important part of the application layer (Akyildiz et al., 2016). The improvement in wireless networks not only enhances the data rate for users but also enhances the chance of connecting more and more devices. From household appliances to vehicles to personal gadgets, everything will be connected via the internet as shown in Fig. 1. The circles in the figure represent the zones of different home gateways comprising various devices connected to the internet via the common access point. IoT has emerged as a promising area, which will decrease the normal life complexities by providing fast and rapid services (Atzori et al., 2010). Also, the connectivity between most of the devices allows efficient control and management. The idea of smart life can be put into practicality with the installation of devices that can form the part of IoT.

Although computerized devices and intelligent systems have been there for a long time, these are not really connected to the real time, thus limiting the amount of knowledge and control over such devices.

* Corresponding author.
E-mail addresses: vishal_sharma2012@hotmail.com (V. Sharma), fsong@bjtu.edu.cn (F. Song), ilsunu@gmail.com (I. You), atiq@ou.edu (M. Atiquzzaman).

http://dx.doi.org/10.1016/j.jnca.2017.08.013
Received 10 May 2017; Received in revised form 5 July 2017; Accepted 28 August 2017
Available online 01 September 2017
1084-8045/

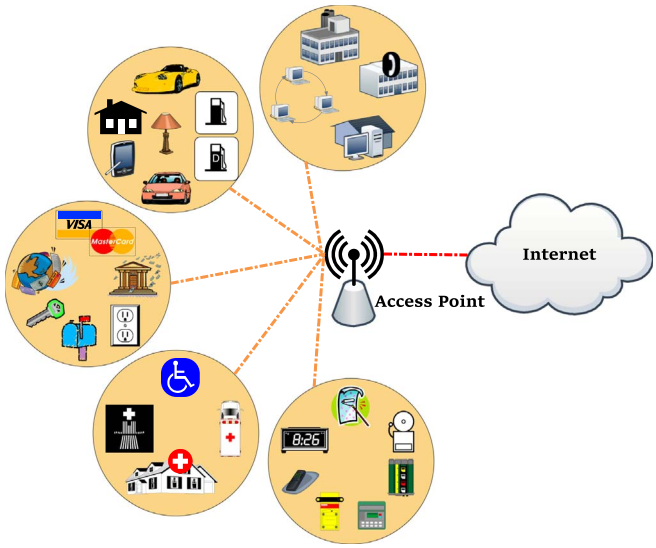

Fig. 1. An illustration of Internet of Things.

But, IoT brings a change in the way such devices will be connected and used (Giang, March et al., 2015). Especially, information processing and availability of control over each device are the key requirements of IoT. Many organizations have already started working on defining the common architectures for the devices that will be a part of IoT. The main focus has been on the development of a common firmware which will facilitate a user to bring a device on the network with ease as well as at low cost (Sharma et al., 2017).

The main difference between BSNs and Wireless Sensor Networks (WSNs) is the design of topology as the sensors are located on a body which serves as a common Region of Interest (ROI) (Lai et al., 2013). An illustration of BSNs is shown in Fig. 2. The design of nodes, placement, fault-diagnosis, data support, reduction in power consumption are the key issues with the BSNs. However, with the continuous demand for data acquisition, designing the low-power rating sensors is the primary focus of researchers. Emphasis on selecting energy-efficient strategies for data dissemination can prevent re-calibrations of sensors.

1.1. 5G-based IoT and BSNs

With the upcoming 5G networks, it will be possible to support a large number of devices in IoT and BSNs simultaneously at higher data rates. IoT and BSNs require separate channel or bandwidth to communicate, which is easily attainable through 5G networks. As stated by Mobile and wireless communications Enablers for Twenty-twenty (2020) Information Society (METIS) (Tullberg et al., 2014), 5G networks are formed by the inclusion of several devices placed in a layered formation such as macrocells, microcells, small cells, femtocells, and picocells. The division of an entire network into smaller

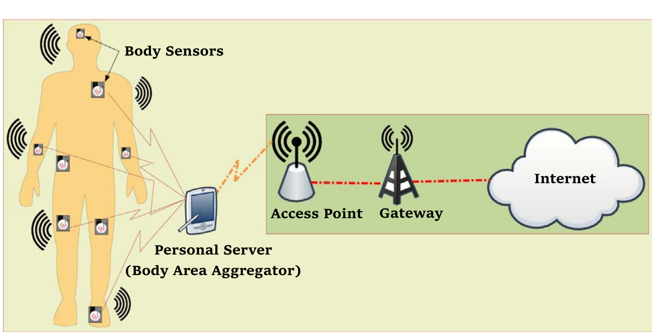

Fig. 2. An illustration of Body Sensor Networks.

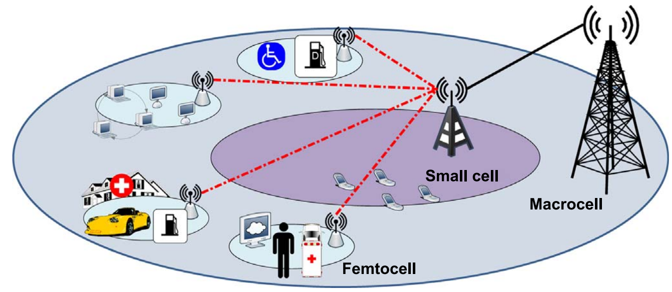

Fig. 3. A representative illustration of 5 G-based IoT and BSNs.

segments allows easy control and coverage over the demand areas. With a large number of access points, more devices and users can be supported with continuous connectivity. Such division of networks can prove handy in handling applications related to IoT and BSNs.

Devices and sensors in IoT and BSNs require continuous, robust and fault-tolerant connectivity for their efficient utilization (Rathore et al., 2016; Galov and Korzun, 2014). The services for managing devices and sensors are at the application layer that interacts with either a femtocell or picocell for network connectivity. The architecture of IoT uses a separate gateway (GW) for connectivity to the core network, whereas the BSN uses a GW and an authentication server (AS) which is connected via femtocells or picocells to the main network. The separate deployment of AS puts a heavy load on a network, which can be managed by using the 5G networks because of its vast capacity and coverage. With minor amendments to initial architecture of IoT and BSNs, the devices and sensors in these networks can be connected to the core network. A representative illustration of 5G-based IoT and BSNs is shown in Fig. 3.

1.2. 5G-based IoT and BSNs using unmanned aerial vehicles

With the advent of 5G networks, the focus has been on the development of standard architectures, which can improve the network range and connectivity. The rising demands of devices can be handled by deploying more number of access points, which itself require new deployment sites and network planning (Sharma et al., 2016a, 2016b, 2015). An alternative to this has been suggested by many researchers, which emphasis on the use of on-demand nodes such as Unmanned Aerial Vehicles (UAVs) for serving as the Access Point (AP) to devices as shown in Fig. 4. Since a lot of researches have been concentrated on the efficient utilization of UAVs in the next generation wireless networks, it becomes important to understand their impact on the services in the IoT, especially in 5G environments.

UAVs can play a key role in the management and control over the 5G-IoT and BSNs by serving as the active gateway to the network. UAVs themselves operate on batteries, which further adds to the issue

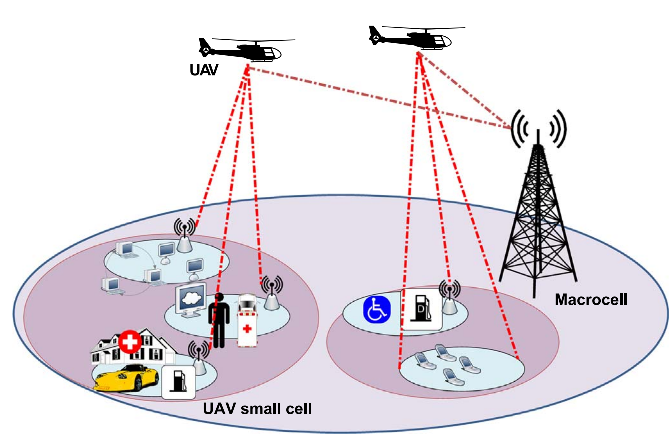

Fig. 4. A representative illustration of 5G-based IoT and BSNs using UAVs.

of energy management in the 5G-based IoT and BSNs. However, efficient resolution of this issue can lead to the formation of a network, which can be better than the traditional architectures suggested for IoT and BSNs (Park et al., 2016; Mozaffari et al., 2016). UAVs can be used to determine the efficient server center which can enhance the services to users and can lower the latency in the case of congestion or sudden increase in the number of end devices in 5G-based IoT and BSNs.

1.3. Energy efficient device discovery

The devices in IoT are operable in continuous mode, thus the overall amount of energy consumption is too high, which may result in power failures for the nodes operating on the battery leading to a large number faults or network shutdown. Device discovery refers to the registration, removal, querying and route formations between the network nodes. With an efficient selection of the next serving hop, the data across the network can be rapidly disseminated. However, with a large number of devices operating together to share the information, the amount of data to be processed on its reception is also very high. The massive reception of data requires efficient processing, which comes at the cost of more consumption of energy resources.

The energy consumed in processing can be optimized to some extent only, but the load and route can be further optimized to select a path which can prevent overload of computations contributing to the formation of a network with high lifetime. Since the network devices in 5G networks are dependent on the battery power, it becomes more important to select devices with an energy-efficient strategy for the formation of a robust and fault-tolerant network. Thus, three major aspects which are crucial for the formation of a reliable 5G-based IoT and BSNs are *fault-tolerant connectivity*, *energy-efficient device discovery* and *efficient offloading*. The network offloading can help reducing the over-consumption of energy over the same device. Further, it is an easy and efficient way to achieve load balancing in the network which can enhance the lifetime of the network. The improvement in these factors allows the formation of a network with better lifetime and vast coverage.

1.4. Motivation, problem statement, and our contribution

The existing approaches for IoT and BSNs primarily focus on the selection of energy efficient route for sharing data so as to enhance the lifetime of the network, but at the cost of transmission capacity and efficiency. The existing solutions are not able to withstand the tradeoff between the energy and transport efficiency of the network. Thus, considering the energy aspects of the devices in IoT and BSNs, the approach should not only provide energy efficient selection of devices and route, but should be capable of handling extra load within the energy limits of the network.

The major limitation of the existing solutions given by Kandhalu et al. (2010); Jiang et al. (2016); Weng and Lai (2013) and Zhou et al. (2015) for efficient device discovery is the no consideration of parameters and features of 5G networks. Sharma et al. (2016c); Yu et al. (2016) and Yoo et al. (2016) considered aerial vehicles to coordinate routing between the sensor networks, but did not focus on the transmission capacity, reliability, and fault-tolerance issues. Further, these approaches did not emphasize much on the offloading which is an important metric in handling energy efficient networks. Thus, the problem deals with the efficient discovery of devices in 5G-based IoT and BSNs with better lifetime as shown in Fig. 5. The lifetime of a network also includes the efficient selection of devices to form a robust and fault-tolerant path which can withstand failures caused by energy breakdowns.

The work presented in this paper uses UAVs to support 5G-based IoT and BSNs. An architecture is developed on the basis of energy and traffic models which allow the formation of a fault-tolerant network

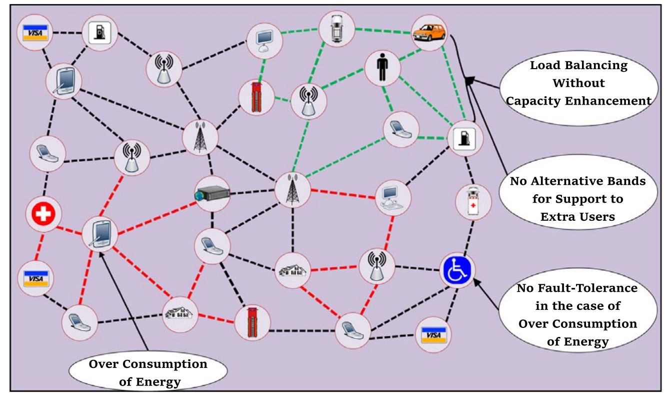

Fig. 5. An illustration of device discovery in 5G-based IoT and BSNs.

that is capable of providing efficient offloading. The proposed architecture offers energy efficient solution for device discovery and load balancing in the network. The key highlights of the proposed work are:

- An energy-efficient architecture for device discovery in 5G-based IoT and BSNs using multiple UAVs.
- Efficient data offloading using on-demand nodes such as UAVs.
- Enhancement of the network lifetime and reduction in per-device energy consumption
- Selection of the energy efficient route between the end devices.

The solution proposed in this paper is capable of reducing energy consumption by 78.4% with 21.3% lower delays and 57.9% lower packet loss. Further, use of UAVs lowers the energy asymptote by 75% and provides more flexibility in implementing energy efficient device discovery.

The rest of the paper is structured as follows: Section 2 gives insights to the related work. Section 3 presents the detailed system, offloading, energy, and fault-tolerant models followed by the energy-efficient architecture for device discovery and theoretical analyses of the proposed approach in Section 4. Section 5 gives simulation results. Finally, Section 6 concludes the paper.

2. Related work

The upcoming 5G networks have attracted a lot of researchers across the globe primarily focusing on the architecture and integration with other network facilities. The 5G network involves hybridization of network components to form a fully reliable network which can enhance the coverage and capacity of the existing networks (Palattella et al., 2016). A classification chart for the literature considered in this paper is shown in Fig. 6. The focus of 5G is on the efficient load management in the network, which enhances the overall quality of services. Device to device communications, data offloading, and use of mmWave in the IoT have further enhanced the utility of these networks (Borkar and Pande, 2016). A detailed overview of the existing state-of-the-art approaches in IoT and BSNs along with their limitations is presented in Tables 1, 2.

2.1. IoT and 5G networks

IoT heavily relies on the device discovery. An efficient discovery approach enhances the flow of information and allows the formation of a network of things which is fault-tolerant and robust. Procedure for query making, selection of the network devices, and the on-demand provisioning of services are the biggest issues in IoT (Guinard et al., 2010). Spiess et al. (2009) worked on the integration of the SOA-based models for IoT. The authors emphasized on the enterprise solutions for service provisioning in IoT. Datta et al. (2014) developed an architec-

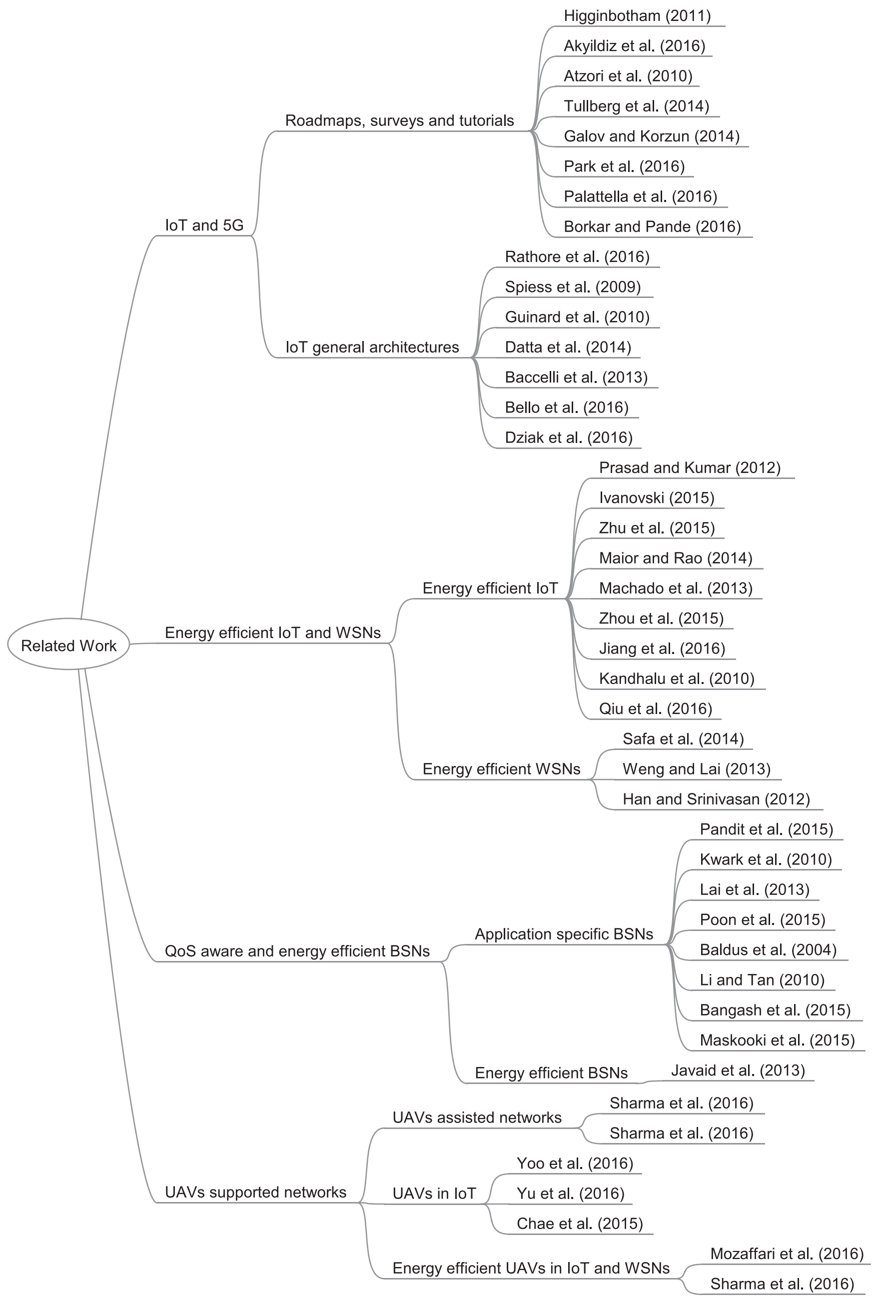

Fig. 6. A broad categorization and application-specific classification of the literature considered in this paper.

ture for the machine to machine communication in IoT. The architecture proposed by the authors uses a centric gateway approach for sharing information across the network.

Baccelli et al. (2013) concentrated on the requirement of an operating system in IoT. The authors demonstrated the utility of multi-threading in the IoT environment for better services and usability. All these approaches aim at provisioning of services to end users without paying much attention to the energy issues related to the service accessibility. None of these approaches focused on the concept of service offloading which can conserve a huge amount of energy. Also, lack of computational energy consumptions makes it difficult to consider these approaches for energy efficient device discovery in a network operating with a diversified number of devices.

Device discovery largely affects the performance of the network as energy consumption of a network depends on the number of devices involved in the sharing of the information. Prasad and Kumar (2012) focused their study on the energy requirements in IoT and presented a study on the Energy Efficiency Reliability (EER) issues. However, evaluating reliability without considering the impact on capacity is a limitation of this approach. Vasilev et al. (2013) studied the reliability of data flow networks in the Smart-M3 platform. The approach developed by the authors allows preserving the context in agent disconnection in the IoT environments. Yu et al. (2014) concentrated on the energy conservation in the pervasive environment. The proposed progressive decentralized single-hop method allows efficient conservation of the overall network energy, which can be used as a practice in the IoT. However, these approaches require detailed evaluation before being considered for IoT networks which operate with a large number of devices.

2.2. Energy conservation in IoT and WSNs

Energy conservation is one of the key aspects of the next generation of networks involving IoT. Ivanovski (2015) presented a detailed study

Table 1
An overview of the existing approaches for IoT and BSNs.

Approach	Ideology	Focus	5G Architecture	Limitations
Rathore et al. (2016)	Smart Cities Using IoT and Big Data Analytics	IoT and Big Data	No	• Limited to smart cities. • Non-energy efficient solutions
Guinard et al. (2010)	SOA-based IoT	IoT	No	• Application interface limited to online use. • Focuses on the interaction with IoT device rather than selecting it. • Non-energy efficient.
Datta et al. (2014)	IoT Gateway Centric Architecture	IoT	No	• Limited to Machine to Machine Communications. • Inefficient discovery phase. • Non-energy efficient. • Non-utilization of network resources.
Prasad and Kumar (2012)	Energy Efficient IoT	IoT	No	• Reliability without analyses of capacity. • Assumes equality in transmission reliability.
Zhu et al. (2015)	Spectrum Sensing in Industrial IoT	Industrial IoT	No	• Probabilistic Approach. • Evaluated only on industrial device simulations.
Dziak et al. (2016)	Interfacing IoT and BSN	IoT and BSN	No	• Focused only on routing. • Reliability and fault-tolerance are not considered.
Baldus et al. (2004)	Reliability in BSN	BSN	No	• No energy management. • Scope limited to medical appliances.
Li and Tan (2010)	MAC for BSN	BSN	No	• Efficient MAC without consideration of consumed energy. • No methodology for sensor search.
Pandit et al. (2015)	MAC for BSN	BSN	No	• Scalability and Fault-tolerance. • No Offloading

on the impact of the energy conservation and gave a solution pertaining to a green computing approach in IoT. Dziak et al. (2016) investigated the device discovery in an alternative way by forming an approach for interfacing the wireless network components as WSNs in IoT. Zhu et al. (2015) proposed an Energy-Efficient Reliable Decision Transmission (ERDT) mechanism for data transmission in industrial IoT. A user classification approach along with the division of the centric server is utilized to provide a reliable communication. Maior and Rao (2014) presented a theoretical framework for the decentralized self-governing IoT with efficient power management. The model developed by the authors utilizes the power demand and priority of a device as a measure to operate the proposed framework. Although these approaches are effective in the environment of testing, there exists a gap between their utilization as these have not been tested in heterogeneous 5G scenarios.

Data dissemination in a network is the measure of the service support provided by the active devices. Inter-network operations play a key role in a device to device communication, which is a crucial part of the IoT networks (Bello et al., 2016). An efficient approach can also reduce the chances of congestion in energy-constrained networks (Leu et al., 2015). There has been a lot of works which have concentrated on the energy optimization while handling the procedures for selection of route between the source and the destination. Machado et al. (2013) proposed a routing strategy for IoT primarily focusing on the energy consumption of the network. The proposed routing by Energy and Link quality (REL) aims at increasing the reliability and energy efficiency of the IoT.

Zhou et al. (2015) developed E-CARP routing strategy for underwater WSNs in IoT. The authors utilized the PING-PONG theory to optimize the energy demands in the existing Channel-Aware Routing Protocol (CARP). Safa et al. (2014) utilized the properties of genetic algorithms to bind together network sensor nodes with efficient energy. The authors focused on the sensor nodes aiming at solving the problem of balancing the load of sensors. Jiang et al. (2016) developed Energy-Efficient Minimum Criticality Routing Algorithm (EEMCRA) for smart cities. The approach developed by the authors optimizes the network's bit energy consumption. Weng and Lai (2013); Weng et al. (2016) developed energy efficient routing algorithm (ERIDSR) and proximity-based routing for sensor networks which is based on the relative identification and direction-based sensor routing (RIDSR) algorithm that in itself is based on the relative direction-based sensor routing (RDSR). These approaches primarily focus on the wireless sensor networks, but not on the BSNs or IoT.

2.3. QoS aware and energy efficient BSNs

BSNs are the crucial part of IoT. BSNs allow implantation of the devices on the body to provide data related to monitoring and physical activity of a user (Poon et al., 2015). The sensors in BSNs can be

Table 2
State-of-the-art approaches for device discovery and routing in IoT and Wireless BSNs.

Approach	Focus	Energy efficient	Fault-tolerant	Offloading	Capacity improvement	UAVs	5G consideration
Kandhalu et al. (2010)	WSNs	Yes	No	No	No	No	No
Jiang et al. (2016)	Smart Cities	Yes	–	Yes	No	No	No
Han and Srinivasan (2012)	ONs	Yes	No	–	–	No	No
Javaid et al. (2013)	BASNs	Yes	No	No	No	No	No
Machado et al. (2013)	IoT	Yes	No	Yes	No	No	No
Weng and Lai (2013)	WSNs	Yes	–	–	No	No	No
Pandit et al. (2015)	BSNs	Yes	–	No	No	No	No
Bangash et al. (2015)	BSNs	Yes	–	No	No	No	No
Maskooki et al. (2015)	BSNs	Yes	–	No	No	No	No
Zhou et al. (2015)	UWSNs-IoT	Yes	–	–	No	No	No
Sharma et al. (2016c)	WSNs	Yes	No	Yes	No	Yes	No
Qiu et al. (2016)	IoT	Yes	No	No	No	No	No
Yoo et al. (2016)	BSNs	Yes	–	No	No	Yes	No

*UWSNs: Underwater wireless sensor networks; ONs: Opportunistic networks; BASNs: Body area sensor networks.

deployed either as an external device or in-body sensor. The connectivity of BSNs over the internet enhances the application of IoT. Baldus et al. (2004) concentrated on BSNs for the medical facilitation of a patient by using on-body sensors. The authors developed a reliable architecture for medical setup as a BSN. Li and Tan (2010) focused on the body sensors primarily targeting the heart beats. The authors developed an active synchronization recovery scheme for the enhancement of the network lifetime. The authors validated their model using OMNET++ simulations. Pandit et al. (2015) gave an efficient MAC protocol for energy efficient data transmissions in the BSNs. The prime focus of their developed scheme is to reduce the overall network delays. Keeping in view the Quality of Service (QoS) of BSNs, Bangash et al. (2015) developed a scheme for data-centric routing. The authors aimed at the enhancement of QoS during intra-body sensors routing. Similar to this concept, Maskooki et al. (2015) developed an adaptive routing for dynamic wireless BSNs. The authors suggested that the adaptive routing strategy can improve the energy efficiency of the network, which will enhance its lifetime. However, these approaches are tested either by using numerical evaluations or simulations without considering the parameters and features of 5G supported BSNs.

2.4. UAVs supported networks

The aspect of using UAVs in the 5G networks has opened many opportunities to enhance their utility. With the use of UAVs as on-demand nodes, better services can be provided to the end devices with the facilitation of link between the source and destination (Sharma et al., 2016a, 2016b). UAVs play an important role in IoT by facilitating the connectivity between the IoT devices and the core network. Recent studies have proved that UAVs can enhance the lifetime of the IoT devices by performing optimized route discovery, thus, saving a huge amount of energy (Mozaffari et al., 2016).

Yoo et al. (2016) studied the utilization of UAVs in IoT. The authors performed flying path optimization for UAVs-assisted IoT. The authors utilized the features of genetic algorithms to facilitate the link between the IoT devices and the UAVs. Sharma et al. (2016c) developed an energy efficient routing strategy for data dissemination (EEDD) in wireless networks operating with UAVs. The authors utilized the properties of the nature-inspired algorithm to find an optimal path between the sensor nodes and the UAVs. Despite these studies and approaches, new approaches are required to bridge the gap between the actual utilization of UAVs in heterogeneous networks especially focusing on the integration of the BSNs and the IoT devices.

Yu et al. (2016) designed an approach for cost-effective security system using UAVs in IoT. Their approach aimed at removing blind spots in IoT by providing secure coverage of an entire environment. Chae et al. (2015) developed an approach for the utility of UAVs in IoT for automatic landing system. Their approach provided automated landing facility with consistent facility surveillance. Peng et al. (2015) also relied on the application of the UAVs for security enhancement in home networks. The existing work has used the drone as an IoT device rather than a facilitating node in the network supporting other IoT devices. This is still an open issue and solutions are required where UAVs can actually be deployed as AP to facilitate the network formation for better coverage and enhancement in the lifetime of IoT devices.

From the literature, it is evident that the existing approaches can provide energy efficient device discovery and routing, but at the cost of bandwidth utilization, transmission capacity and spectral efficiency. The existing solutions are not capable enough to withstand the tradeoff between energy and transport efficiency. It is also clear that UAVs can play an important role in device discovery with enhancement in the lifetime of the network. However, there is a lack of an approach that has considered a 5G-based IoT and BSN scenario together with assistance from UAVs for the enhancement of network lifetime and fault-tolerance. Thus, in this paper, an energy efficient architecture is proposed which supports the UAVs in 5G networks to optimally perform device discovery and routing between the IoT devices and the BSNs. The proposed approach is also able to handle the tradeoff between the energy efficiency, transmission capacity and network offloading.

3. System model

The proposed approach allows energy efficient device discovery in the 5G-based IoT and BSNs using multiple UAVs. Firstly, we present the initial system model, traffic model, and then evaluate the energy paradigms over the initially defined system model. Secondly, the variations in the asymptotes denoting the tradeoff between the energy efficiency, network offloading and network transmission capacity are presented.

3.1. Network model

The network comprises an area A divided into a series of macrocell denoted by set M. These macrocells serve as the gateway to all the IoT and BSN devices for communicating across the other cells. The network utilizes the features of 5G deployment, which comprises a set F of femtocells which are the HeNB for the network. The femtocells support the formation of a network between the body sensors and provide connectivity to the IoT. Let W be the set of small cells, which form the middle layer between the macrocell and the femtocells. In order to provide on-demand support for connectivity between the macrocell and the femtocells, a set U of UAVs is deployed in which UAVs form their own small cells termed as "UAV small cell".

The small cell formation using UAVs allow better coverage as well as better connectivity since UAVs can be deployed on-demand, thus, resolving CAPEX/OPEX in the 5G networks. The entire network comprises a set V of sensors supporting BSN as well as IoT. Along with BSN, the proposed model also supports end users, which are termed as User Equipment (UE). Let R be the transmission rate of the network (Shannon and Weaver, 2015) given as:

$$R = r\,\mu, \tag{1}$$

where r is the number of messages transmitted per second and μ is the message size. Now, the load L over a macrocell in a set M is given as:

$$L = \int_{A_M} \frac{R}{C} dA_M, \tag{2}$$

where C is the network capacity Sharma et al. (2016a) given as:

$$C = \omega \log_2(1 + SINR), \tag{3}$$

where ω is the system bandwidth and $SINR$ is the signal to interference plus noise ratio (Shannon and Weaver, 2015). Here S is the signal power and N is the noise power. Also,

$$SINR = \frac{\frac{\rho h}{d^{\alpha}}}{\sum_{i=1, i\in f(\lambda)}^{|X|} \frac{\rho h}{d^{\alpha}} + N}, \tag{4}$$

where ρ is the transmission power, h is the characteristic constant for antenna type, d is the distance between the nodes, α is the path loss exponent, $f(\lambda)$ is the distribution of the nodes for which SINR is calculated, and N can be further expressed with respect to spectral density η and bandwidth such that $N = \eta\,\omega$ (Shannon and Weaver, 2015). $f(\lambda)$ is derived over the set X, which comprises nodes from the sets M, U, F, W, V; and for the evaluation over entire network, X={x: x are the nodes from $M \cup U \cup F \cup W \cup V$ which are active}. Now, let γ be the maximum intensity of attempted transmission, such that the transmission capacity T_c of the system considering within the outage probability ϵ (Jindal et al., 2007) is given as:

$$T_c = \gamma(1 - \epsilon)Q, \tag{5}$$

where the spectral efficiency Q of the network operating with B number of channels is given as:

$$Q = \frac{\omega \log_2(1 + SINR)}{B}, \tag{6}$$

and using the definition of transmission capacity from Jindal et al. (2007),

$$\gamma = \frac{q}{\pi d^2}\left(\frac{1}{SINR} - \frac{N}{\rho d^{-\alpha}}\right)^{\frac{2}{\alpha}} \epsilon + O(\epsilon^2), \tag{7}$$

where O (ϵ^2) is the upper bound of the outage probability and q is the fading constant.

3.1.1. Traffic model

Considering the transmission rate R, it is observed that this gives the maximum transmission rate over the channel with capacity C. Now, this can be attained in the ideal case, but for other cases, the arrival rate of the nodes and the connection at a particular instance affect this rate. The proposed approach is inspired from using UAVs as one of the key nodes to support the network with better connectivity to allow energy efficient device discovery in 5G-based IoT and BSNs. The maximum data shared in the network depends on the condition of "Probability of maximum data needed to be shared". Thus, if P_{data} is the probability of the data shared between the nodes, then the network focuses on optimizing this probability to attain a maximum. This data rate attained is dependent upon the number of links L active in the network. Thus, P_{data} maximizes if L attains maximum. For a network, the maximum value of L can be $\frac{|X|(|X|-1)}{2}$. Now, considering the arrival rate of the messages over a single channel, it is assumed that the traffic of the network will increase exponentially in the 5G-based IoT and BSNs. Thus, the traffic is given as a function $H(t)$ (Dua et al., 2016) such that:

$$H(t) = re^{-rt}. \tag{8}$$

Now, for entire transmission time T, the probability of transmission is given as:

$$P_{data}(r) = \int_0^T re^{-rt}dt \tag{9}$$

$$=1 - e^{-rT}. \tag{10}$$

In the network with a B number of channels, the probability of maximum traffic, considering the maximum number of channels, is given as:

$$P_{data}(r_B) = 1 - e^{-(r_1+r_1+\cdots+r_B)T}. \tag{11}$$

The proposed approach is supported by extra links which are provided by the on-demand deployment of UAVs. The set U of UAVs allows efficient network formation with enhanced traffic such that, considering the model defined in Eqs. (8)–(11), the probability of traffic supported using UAVs is given as:

$$P_{support}(|U|) = 1 - e^{-(|U_1|+|U_2|+\cdots+|U_k|)T} \tag{12}$$

where k is the number of UAVs available to support the network such that $k \le |U|$. It can be concluded from Eq. (12) that with more number of channels, the probability of transmission increases. With $|V| + |U|$ being the active nodes in the network making continuous requests with different bandwidth, the network is divided as $\frac{\omega}{|V|+|U|}$, and the available active links L_a are $\omega\left(\frac{1}{B} - \frac{1}{|V|+|U|}\right)$. Thus, for the entire network to be in a state of continuous transmission, $\frac{L_a}{|V|+|U|} \ge 1$. At any instance during transmission, if $\frac{L_a}{|V|+|U|} < 1$, the network users are not handled and there is a packet loss or congestion. Thus, to optimally handle the network, k i.e. the number of channels considering a single channel over each UAV, should be greater than equal to $\frac{L_a}{|V|+|U|}$. It is to be noticed that availability of channels is a measure of network capacity, which does not guarantee a fault-tolerant transmission. Thus, the performance of the network will depend on the capacity, traffic rate, bands available, and the energy utilization of the network.

3.1.2. Energy model

For a general network, the energy per bit is given as the ratio of the signal power to the capacity of the network i.e $E = \frac{S}{C}$. Although energy per bit of a network can be calculated during pre-configurations, the proposed model utilizes the energy consumption per link in the entire network. Using the link-based energy consumption, an energy graph is formed, which allows identification of zones with over as well as underconsumption of energy resources during the device discovery. For this, the energy model from a tradeoff analyses presented by Bae and Stark () is used, according to which E_{tx} is the transmitter energy, E_p is the receiver processing energy such that the overall energy required to share data between any two nodes in the network is given as:

$$E_t = E_{tx} + E_p \tag{13}$$

However, for link based energy consumption, the total energy depends on the per bit energy consumption and intermediate hopes (Li et al., 2012; Jumira and Zeadally, 2012) and is given as:

$$E_t = E_{tx} rd^\alpha + E_p rI + \sum_{i=1}^{I-1} E_{t,i}, \tag{14}$$

where I is the number of intermediate nodes causing interference to the used channel such that I belongs to the function $f(\lambda)$ showing node distribution in the network. Now, from Shannon and Weaver (2015),

$$E_t = \frac{S}{C} = \frac{S}{QB} \because Q = \frac{C}{B} \tag{15}$$

$$\Rightarrow E_t \propto \frac{1}{Q} \tag{16}$$

From Eq. (15), it can be noticed that the higher spectral efficiency can be attained only at the verge of high consumption of per bit energy. A lower energy decreases the signal quality and causes a high impact on the formation of an energy-efficient strategy for device discovery in the 5G-based IoT and BSNs. This can be overcome by managing the asymptotic behavior of the network as given by Shannon and Weaver (2015). According to the network energy conditions,

$$\frac{C}{\omega} = \log_2\left(1 + \frac{S}{N}\right) \tag{17}$$

$$\frac{QB}{\omega} = \log_2\left(1 + \frac{S}{N}\right) \because Q = \frac{C}{B} \tag{18}$$

Therefore using Eq. (15),

$$\frac{E_t}{\eta} = \frac{\omega}{QB}\left(2^{\frac{QB}{\omega}} - 1\right) \because N = \eta\omega. \tag{20}$$

Thus, asymptote for energy model considering the Shannon limit (Shannon and Weaver, 2015) follows:

$$\frac{E_t}{\eta} \propto \frac{1}{Q}. \tag{21}$$

For an optimized solution to a network operating with different kinds of devices, the bandwidth is pre-defined and the rate depends on the spectral efficiency and the transmission capacity of the network, which itself depends on the maximum intensity of transmission. Thus, the upper bound over maximum intensity can be ignored since it remains the same for entire network (Jindal et al., 2007) and the remaining part is to be optimized, such that Eq. (7) becomes:

$$\gamma = \frac{q}{\pi d^2}\left(\frac{1}{SINR} - \frac{N}{\rho d^{-\alpha}}\right)^{\frac{2}{\alpha}}\epsilon. \tag{22}$$

Now, for interference oriented analysis, $\frac{N}{\rho d^{-\alpha}}$ becomes negligible effective and can be ignored while understanding the asymptotic behavior of the network (Jindal et al., 2007). Therefore, Eq. (22) deduces to

$$\gamma = \frac{q}{\pi d^2}\left(\frac{1}{SINR}\right)^{\frac{2}{\alpha}}\epsilon \tag{23}$$

$$= \frac{q}{\pi d^2}\left(\frac{N}{S}\right)^{\frac{2}{\alpha}}\epsilon \tag{24}$$

$$= \frac{q}{\pi d^2}\left(\frac{\eta\omega}{E_t QB}\right)^{\frac{2}{\alpha}}\epsilon \tag{25}$$

Thus, by rearranging,

$$\frac{E_t}{\eta} = \frac{\omega}{QB\gamma^{\frac{\alpha}{2}}}\left(\frac{\pi d^2}{q\epsilon}\right)^{\frac{-\alpha}{2}}. \tag{26}$$

Now, at constant rate, the spectral efficiency and bandwidth of the network remain same, thus, the asymptote is defined as:

$$\frac{E_t}{\eta} \propto \frac{1}{\gamma^{\frac{\alpha}{2}}}. \tag{27}$$

Considering the variation in the rate, the asymptote will be at:

$$\frac{E_t}{\eta} = \frac{\omega\gamma(1-\epsilon)}{T_c B}\left(\frac{\gamma\pi d^2}{q\epsilon}\right)^{\frac{-\alpha}{2}}. \tag{28}$$

and at constant intensity using Eq. (20), the asymptote is at

$$\frac{E_t}{\eta} = \frac{1}{\delta T_c}(2^{\delta T_c} - 1) \because N = \eta\omega, \tag{29}$$

where

$$\delta = \frac{B}{\omega\gamma(1-\epsilon)}. \tag{30}$$

Therefore,

$$\frac{E_t}{\eta} \propto \frac{1}{T_c}. \tag{31}$$

3.1.3. Fault-tolerance model

Fault-tolerance refers to the operations of a network under crucial circumstances like node failures or depletion of network resources. How a network operates in these conditions allow measurement of networks' fault-tolerance. An efficient network can prove to be robust and fault-tolerant if it withstands the network failures without service breakdown. In the work presented in this paper, three main aspects are considered as the driving properties for fault-tolerance, namely, node reliability, power reliability and route reliability. All these properties jointly decide the stabilization state for a network, which helps in efficient device discovery even in the case of network failures. The network fault tolerance is given as a state cost C_s, which is calculated as:

$$C_s = \frac{w_1 f_1 + w_2 f_2 + w_3 f_3}{w_1 + w_2 + w_3}, \tag{32}$$

where w_1, w_2, and w_3 are the weights defining the impact of a property on the state cost. The weights are taken in the range of 0–1 depending upon the priority set for a particular property. The values of weights affect the performance depending on the dominance of their respective function. In the proposed approach, the values for weights are kept constant and divided equally on the defined scale. This helps in maintaining similar precedence for every function and allows balanced analysis of the proposed approach.

The proposed network model relies on reliability to identify the state of fault-tolerance in a network (Shooman, 2003). A highly reliable network is fault-tolerant, thus, these functions in (32) are defined in terms of reliability. Here, f_1 is the node reliability given as:

$$f_1 = \sum_{i=\min(|X|)}^{|X|} P_{n,i} \tag{33}$$

$P_{n,i}$ is the probability of node being operational, and $\min|X|$ denotes the minimum number of nodes required to keep a network active with its upper limit being $|X|$.

$$f_2 = \sum_{i=\min(|X|)}^{|X|} P_{n,p,i} + \sum_{i=\min(|L|)}^{L_a} P_{L,p,i} \tag{34}$$

where $P_{n,p,i}$ is the probability of nodes possessing the minimum required power for transmission and reception of packets, and $P_{L,p,i}$ is the probability of link possessing sufficient power to continue transmission.

$$f_3 = \sum_{i=\min(j)}^{\frac{|X|(|X|-1)}{2}} P_{L,i} \tag{35}$$

where $P_{L,i}$ is the probability of an availability of routes in the network and j is the number of minimum routes required for a network to sustain. The higher cost of the network means more robust and fault-tolerant connectivity. From (34), it is to be noticed that the power condition has much impact on the fault tolerance. Thus, a network with better utilization of energy resources will be more applicable for the selection of fault-tolerant routes between the devices. The minimum value of nodes required for the continuous operations of the network can be defined by a graph $G = (V', Z)$, where V' is the minimum number of active nodes, and Z denotes the minimum number of active routes. For efficient connectivity, a node should never be isolated. A network should be aware of the maximum number of available routes to connect all its vertices. The network fault-tolerance can be presented in terms of degree of connectivity of a graph G, which is equal to $\theta + 1$, where θ forms the out-degree with at least one in-degree. Network devices will be isolated if the link failure is found due to power failures or overconsumption of network resources. This isolation can be determined by the fault-tolerance cost given in Eq. (32).

In contrast to this, energy-asymptote of Shannon limit is used to determine the fault-tolerance level of the network by identification of $\frac{E_t}{\eta}$ at any instance, which serves the lower limit below which there is a high probability of network faults and errors Shannon and Weaver (2015). For maximum connectivity, a node can have maximum of $|X| - 1$ connections, i.e. $(\theta + 1) \leq (|X| - 1)$. If $(\theta + 1) = (|X| - 1)$, then the network will be highly fault-tolerant and robust, with a high percentage of network offloading, but with much consumption of energy. Thus, an optimal point is required to be selected on the basis of C_s, where the network can guarantee a similar level of offloading and spectral efficiency, but with less consumption of energy resources. Further, the increase in the degree of connectivity also increases the percentage redundancy, which also affects the amount of energy consumed in the network. In a network comprising $|X|$ active devices with each device having at least $\theta + 1$ connections, the network redundancy is given as $(|X|(\theta + 1)) - |X| + 1$ Wu and Chao (2004). The amount of network redundancy helps to understand the alternative paths available for routing between the devices, which supports an intelligent decision for the formation of an energy efficient as well as a fault-tolerant network of things.

4. Proposed architecture for energy efficient device discovery

The selection of the device in the 5G-based IoT and BSNs depends on the conditions given in the previous section, such that the network is always in an optimized state. The proposed approach provides UAVs-assistance for searching devices in the network which can efficiently maintain the flow and can be used for offloading. The proposed approach balances the load and allows the formation of an energy efficient, robust and fault-tolerant model for data transmission across the network. The aim of the proposed approach is to optimize the network energy by selecting the appropriate devices which allow improved load balancing and prevent the network from going into a state of low energy. The optimization problem deals with following aspects:

- To minimize the overall consumption of energy without affecting the SINR, i.e. $\min(E_t)$.
- To improve the network offloading with less consumption of network resources, i.e. $\max(P_{support})$.
- To improve the network fault-tolerance by maximizing the state cost and number of active links, i.e. $\max(C_s)$ and $\max(L_a)$.

The proposed approach follows the principle of "Critical Area" to check for network parameters and configurations before taking any decision on the route. All the entities in the network are subjected to common functional architecture, which regulates the working of all the devices in the underlying layer on the basis of energy requirements.

An illustration of the functional architecture is shown in Fig. 7. This architecture gives each node a complete overview of the energy and fault-tolerant state for every device connected to the network. The architecture comprises a "Network Configurations" unit, which is responsible for setting the configurations of each node for transmission and reception of packets. A node uses this feature to alter its parameters during any time in the network. A node can use the network configurations unit to make pre-hand identification of the network requirements, and can instruct other devices regarding its policies through network advertisements.

Next, the architecture contains a "Utilizer Layer" which incorporates the proposed energy, fault-tolerance, and offloading model to sustain the network operability without any flaw. All these models are jointly operated on the basis of optimization conditions in a "Decision System" which generates the final values for each metric in the network which will optimize the selection of the next device.

The values generated from the decision system can be monitored by using a "Value Analyzer". Any value causing the network to go into the dead state can be identified early and the configurations and parameters decided by each node can be *reset* to save time and energy, which otherwise would have been consumed in transmitting packets with no guarantee of reception by any network device. In the case of satisfaction of values from the decision system, a "Comparative Value Generator" is invoked, which compares the values of the parameters of a particular node with the ones received from the other devices. It also allows identifying the devices which can support the similar configurations as set by the node for communication.

This comparative generator works in coordination with the entire network and uses the same channel for information sharing as that used during the transmission. To prevent packet overhead, the functional architecture relies on the configuration packets rather than using the same packet with more values. It is to be noted that the UAVs are used similarly to other access points allowing the formation of UAV-small cells. The explanation to this is already provided in network setup (Section 3.1).

Theoretically, it looks to add up some extra delay, but the configuration packets can be floated only at a certain time. This time can be set on the basis of C_s. A threshold can be set for the state cost and whenever the network reaches the critical area, which is the threshold of the C_s, the nodes resend the configuration packet to acquire current state information of the entire network. Thus, the proposed approach is capable of selecting the device applying to energy constraints of the network.

The decision system of the functional architecture relies on a simple algorithm to resolve the selection of next device as well as for advertising network policies and maintaining a check on the critical area. Algorithm 1 gives the steps for device discovery using decision system of the proposed functional architecture, whereas the Algorithm 2 includes the sub-procedures for finding the energy efficient path and offloading.

Algorithm 1. Decision System For Device Discovery.

1: **Input**: M, U, F, W, V
2: Initialize Network, send configuration packets, adj[]
3: Calculate current P_{supprt}, E_t, C_s

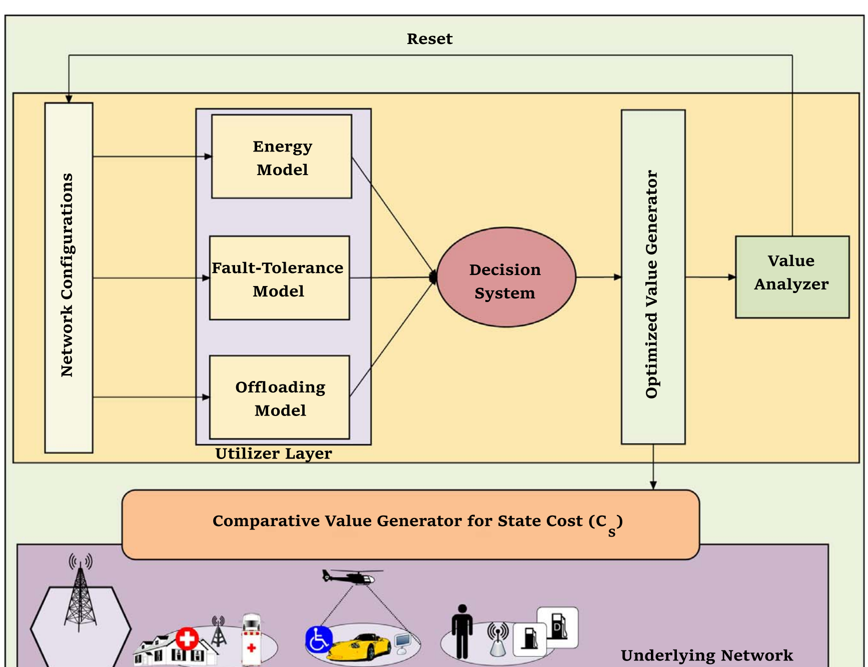

Fig. 7. Functional architecture for efficient device discovery.

set $E_{min} = \min(E_{tx}) + \min(E_p)$
Set C_s^{TH}
i = 1
while $i \le |X|$ **do**
  if $E_t(i) \ge E_{min}$ **then**
    $V' = i$
    if $C_s \le C_s^{TH}$ **then**
      resend configuration packets
    else
      store V' in adj[]
      calculate $P_{support,i}$
    end if
  end if
  path[] = route(adj[],source,destination)
  check for nodes with $E_t < E_{min}$
  mark as dead
  delete from adj[]
  i = i+1
end while
transmit over path[] for offloading

Algorithm 2. Offloading and Routing For Device Discovery.

Input: source, destination, adj[]
sort(adj[],'descend:energy')
x = position of destination in adj[]
set counter = 0
route = adj[1:x]
i = 1
while $i \le x$ **do**
  if $E_t(i) \ge E_{min}$ & & $P_{support,i} = \max$ **then**
    g[] = mark i for offloading
    delete i from adj[]
  end if
  route[] = adj[]
  counter = counter + 1
  i = i + 1
end while
return g[1]

The Algorithms 1 and 2 operate together for finalizing the route between the discovered devices as well as for offloading. The offloading helps in balancing the network load by providing an alternative path with high availability of energy. This process leads to equivalent usage of network energy, thus, forming a network which can sustain for longer duration and can offer better lifetime. The Algorithm 1 evaluates the minimum requirement of the energy and the current state of the network to analyze the frequency of transmitting the configuration packets. The higher frequency of configuration packets refers to more wastage of energy in device discovery, whereas a low value provides better support by the network.

A state of the network with a minimum number of configuration packets and high offloading is referred as the perfect and stabilized state. This is easy to attain theoretically, but for the practical environments, such equilibrium is difficult and can be attained by relaxing the limits on some of the parameters. Algorithm 1 operates for the number of nodes active in the network, whereas the Algorithm 2 operates for the position of the destination node in the adjacency matrix in the rank of available energy. In the worst case, the position of the destination in the energy chart is at lowest requiring at least n iterations, whereas the Algorithm 1 undergoes $|X|$ iterations despite the rank of destination.

If all the nodes have energy greater than the minimum required along with destination at the lowest rank, the algorithm traverses through each node, which is a worst case; and thus, time complexity in the worst case becomes $O(n^2)$. However, the average case will be the destination having energy greater than some of the nodes, whereas for the best case the destination will be on the top of the energy chart. In both the cases, the initial algorithm (Algorithm 1) will undergo same iterations as the worst case whereas the Algorithm 2 will operate in log time, which makes the overall time complexity be $O(n \log n)$. These complexities are calculated by following the running time for each function and loops in the proposed algorithms.

This complexity is capable of sustaining any network size and can be used even if the number of devices increases continuously. Also, it is to be kept in mind that with the use of UAVs, a large number of nodes will be available for offloading, which distributes the energy utilization equally for the entire network. The equal distribution and efficient offloading allow the formation of a robust and fault-tolerant network which will guarantee better lifetime than the traditional IoT and BSNs operating with dependency only on the static APs.

4.1. Formation of the energy charts

An energy chart is maintained by each node for routing and device discovery. The energy chart helps to regain the routes and decisions for selecting the nodes even if the configuration packets fail. Further, the energy charts are used to continue transmission until the requirement of updates for next configurations from network devices. The energy charts keep a record for the five major contents, namely, next hop, number of intermediate links, energy consumption rate, available energy, and networks' state cost, as shown in Fig. 8. The parameters required for XML formations are shared as configuration packets as discussed in the architecture.

Each node has its own chart stored in the form of XML sheets. For smooth functioning and better offloading, devices in the network can share these charts among themselves resulting in a formation of fully-aware IoT and BSNs. This feature also helps UAVs to identify areas with a requirement of more access points by reading the energy values. UAVs can take a decision to identify the locations where the energy consumption is likely to get too high, which may result in a dead state.

```xml
<?xml version="1.0" encoding="UTF-8" ?>
<NodeParent>
        <Nodeadj>
                <Nodeid>1</Nodeid>
                <Hops>2</Hops>
                <Energy>C_Rate</Energy>
                <EnergyLeft>E_t</EnergyLeft>
                <StateCost>C_s</StateCost>
        </Nodeadj>
        <Nodeadj>
                <Nodeid>2</Nodeid>
                <Hops>3</Hops>
                <Energy>C_Rate</Energy>
                <EnergyLeft>E_t</EnergyLeft>
                <StateCost>C_s</StateCost>
        </Nodeadj>
        <Nodeadj>
                <Nodeid>3</Nodeid>
                <Hops>4</Hops>
                <Energy>C_Rate</Energy>
                <EnergyLeft>E_t</EnergyLeft>
                <StateCost>C_s</StateCost>
        </Nodeadj>
</NodeParent>
```

Fig. 8. An illustration of the energy chart.

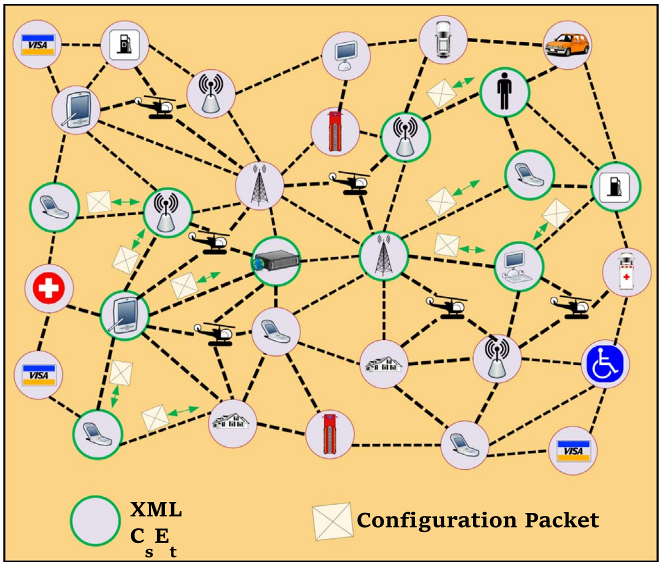

Fig. 9. An illustration of network flow diagram for proposed procedure in UAVs supported 5G-based IoT and BSNs.

Thus, use of energy charts can prevent the devices from going into dead state, as well as can prevent areas from losing connectivity during the peak hours.

An overview of the proposed approach for device discovery in 5G-based IoT and BSNs using UAVs is shown in Fig. 9. Since every node in the network defines its own energy chart and uses it for device discovery, there may be a situation of congestion due to excessive flow of charts in the network. Such situations can be prevented either by using an on-demand agent for sharing the energy charts or by defining multiple bands per channel. The proposed Algorithms 1 and 2 take care of such situations and use a decision system for identifying the nodes from whom the energy charts are required. The offloading paradigm in the paper helps in resolving the issues related to the congestion due to excessive energy charts. Further, with deployment of UAVs as on-demand small cells, these congestions can be optimally resolved following the trivial principles of load balancing.

4.2. Theoretical analyses

This part presents the theoretical aspects of the proposed approach, which emphasizes on the use of UAVs for saving energy and increasing offloading in the 5G-based IoT and BSNs.

Lemma 1. *With an increase in the number of nodes serving the same set of devices, the probability of data offloading maximizes* i.e. $P_{support} = \max$ *if* $|U|$ *increases.*

Proof. From Eqs. (9)–(12), considering an exponential arrival for the number of UAVs, the equation can be modified as (Dua et al., 2016):

$$P_{support} = \int_0^T Ze^{-Zt}dt, \tag{36}$$

where Z is the number of links available for each of the device given as $Z = \frac{|U|(|U|-1)}{2}$. Clearly, $P_{support}$ maximizes with an increase in the number of links, hence, proving the condition stated in the Lemma. With a large number of nodes serving the same set of devices, the usage of energy can be equally shared, which results in the lower consumption of energy over a single node. Thus, more devices can provide better offloading which in turn reduces the per node energy consumption. □

Lemma 2. *The average energy consumption per device increases with an increase in the network offloading, but this increase can be controlled by using UAVs as alternative nodes.*

Proof. From Eqs. (1), (8) and (9), the probability of transmission is given as:

$$P_{data} = \int H(t)dt \tag{37}$$

which is calculated for the entire duration, such that

$$P_{data} = \int_T \frac{R}{\mu} e^{-\frac{R}{\mu}t}dt \tag{38}$$

$$=1 - e^{-\frac{ST}{\mu E_t}} \tag{39}$$

From Eq. (38), it can be noticed that if the probability of maximum data supported by the network increases, $1 - e^{-\frac{ST}{\mu E_t}}$ maximizes. This means $e^{-\frac{ST}{\mu E_t}}$ becomes too small and this makes the energy consumption too high. Thus, if the network offloading increases without an increase in the number of alternative links, the energy consumption of the network also increases, which raises a serious tradeoff between the energy efficiency and the network offloading capacity. However, with an increase in the number of nodes (on-demand), the number of connections increases for a single device, which decreases the amount of energy consumption per bit on a single channel as $E_t \propto \frac{1}{B}$. Thus, it can be concluded that the increase in the network offloading occurs on the verge of a decrease in the energy efficiency of the network, but this can be controlled by using more number of UAVs as this increases the number of channels, which decreases the per bit energy consumption on each channel. □

Theorem 1. The involvement of UAVs shifts the energy asymptote, which attains a lower value if all the deployed UAVs are actively supporting the network.

Proof. Let B be the initial number of channels available before deployment of UAVs and $|U|$ be the number of extra channels (considering single channel per UAV), then the two asymptotes are given as (from Eq. (28)):

$$\frac{E_t}{\eta} = \frac{\omega}{QB}\left(\frac{\pi\gamma d^2}{q\epsilon}\right)^{\frac{-\alpha}{2}} \tag{40}$$

and

$$\frac{E_t{}'}{\eta'} = \frac{\omega}{Q(B+|U|)}\left(\frac{\pi\gamma d^2}{q\epsilon}\right)^{\frac{-\alpha}{2}}. \tag{41}$$

The difference of the asymptotes is given as:

$$\frac{\Delta E_t}{\Delta\eta} = -\frac{\omega|U|}{BQ(B+|U|)}\left(\frac{\pi\gamma d^2}{q\epsilon}\right)^{\frac{-\alpha}{2}}. \tag{42}$$

Negative sign represents the increase in lower limit, which lowers the energy-asymptote of the network. Considering the entire network to be operating at a constant value, the shift in the asymptote is given as:

$$\frac{\omega}{Q(B+|U|)}\left(\frac{\pi\gamma d^2}{q\epsilon}\right)^{\frac{-\alpha}{2}} \leq \frac{\Delta E_t}{\Delta\eta} \leq \frac{1}{B} \tag{43}$$

Thus, from Eq. (43), it can be concluded that the addition of extra UAVs as a support to the IoT devices lowers the Shannon limit, which in turn increases the performance and capacity of the network without much increase in the per link energy during transmission. □

5. Performance evaluation

The proposed approach provides an energy-efficient strategy for device discovery in 5G-based IoT and BSNs using UAVs. The proposed approach utilizes the XML energy charts to perform data forwarding along with the increase in the performance of the network in terms of the energy consumption, data offloading, and fault-tolerance. The evaluation of the proposed approach is presented in two parts. The

Table 3
Parameter Configurations For Numerical Analyses.

Parameter	Value	Description
$\|M\|$	1	Analyses around single macrocell
$\|U\|$	20 (per MBS)	Number of UAVs
$\|F\|$	10^4	Number of femtocells
$\|V\|$	10^4	Number of body sensors
$\|W\|$	10^2	Number of Small Cells
η	− 174 dBm/Hz	Noise Power Spectral Density
ω	10 MHz	System Bandwdith
$\min(R)$	256 kbps	Offered Traffic
α	2–4	Path loss Exponent
h	− 11 dB	Transmission Constant
ρ	35 dBm	UAV Transmission Power
ϵ	0.1	Outage Probability
q	1	Fading constant
d	200 m	Radio range
E_{tx}	0.5 J	Transmitter Energy
E_p	0.25 J	Receiver Processing Energy
B	1–20	Number of sub-bands(single channel)
w_1, w_2, w_3	0.33	Weights for state cost

first part evaluates the approach numerically, whereas the second part presents the comparative analyses using simulations with the existing state-of-the-art approaches.

5.1. Numerical analyses

The proposed approach is evaluated numerically for variations in the offloading and asymptote behavior with and without the use of UAVs in the 5G-based IoT and BSNs. The symbol notations and their values for numerical analyses are presented in Table 3. Numerical analyses are conducted by following the standard values for parameters as defined in Refs. (Sharma et al., 2016a; Mozaffari et al., 2016; Merwaday and Guvenc, 2015). These analyses are performed with prefixed values and minor assumptions, such as non-dependency on the type of UAVs and IoT devices, which can be altered to analyze the performance of the proposed approach in different modes.

The proposed approach is evaluated for offloading capability, transmission capacity, energy asymptotes and state cost variations. These factors are affected by the number of UAVs deployed as well as the number of sub-bands available per channel over each aerial vehicle. Data offloading via formation of energy charts is the key feature of the proposed approach. The number of properties stored in these charts affects the load as well as the performance of the proposed approach. However, in the present state, the energy charts, as explained earlier, operate with a limited set of parameters and do not affect its performance.

5.1.1. Offloading variations

The proposed approach is capable of supporting single and multiple channels over UAVs. The result in Fig. 10 shows that the proposed approach enhances the probability of data offloading with the increase in the number of UAVs. However, the variation in the number of channels and active links affect the performance of the network. The results show that with more active channels and an increase in the number of UAVs, the probability of data offloading increases by 24.4%. The similar effect is noticed even at 10% failure rate in the number of active devices as shown in Fig. 11.

5.1.2. Transmission capacity variations

According to Eq. (5), the transmission capacity of the network plays a crucial role in achieving the desired rate, which can withstand the offloading demands of the network. As stated in the system model, the network behaves differently with and without the inclusion of interference-free SNR. The variations due to interference-free SNR are

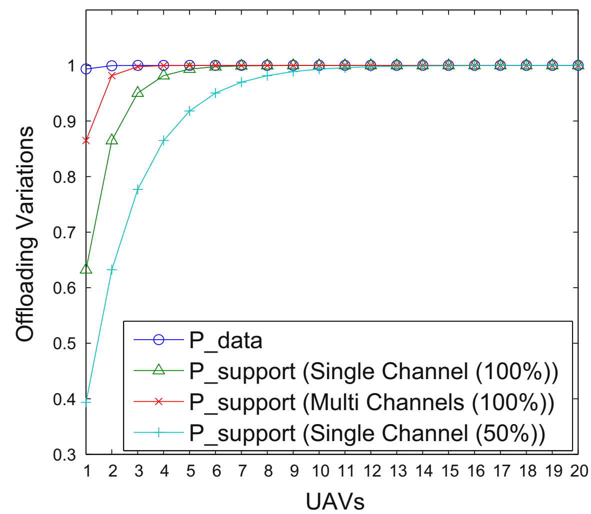

Fig. 10. Offloading variations vs. UAVs.

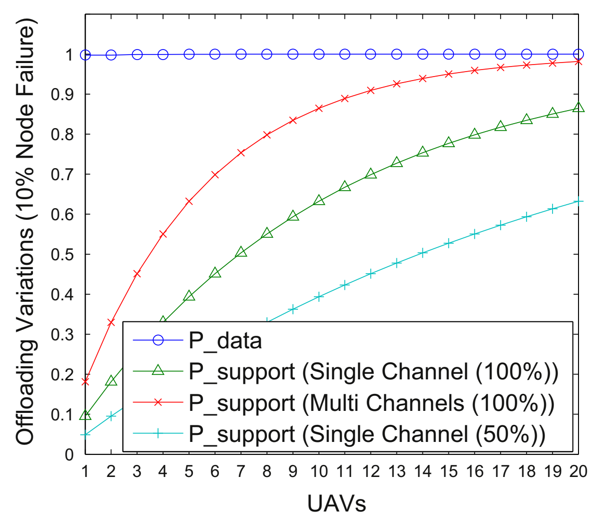

Fig. 11. Offloading variations at 10% node failure vs. UAVs.

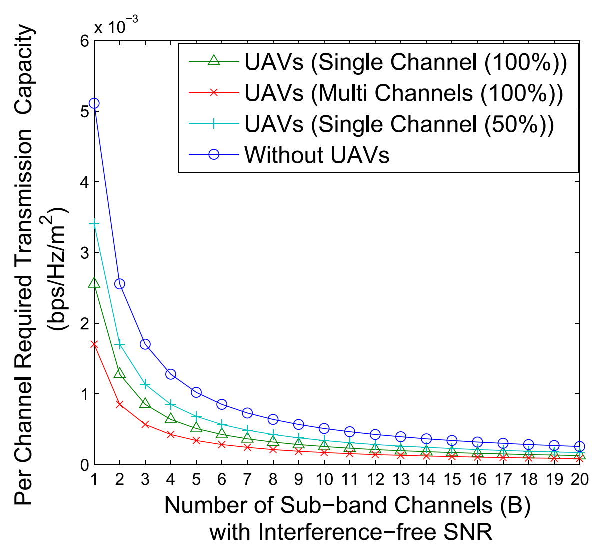

Fig. 12. Per channel required transmission capacity vs. number of sub-band channels (B) with interference-free SNR.

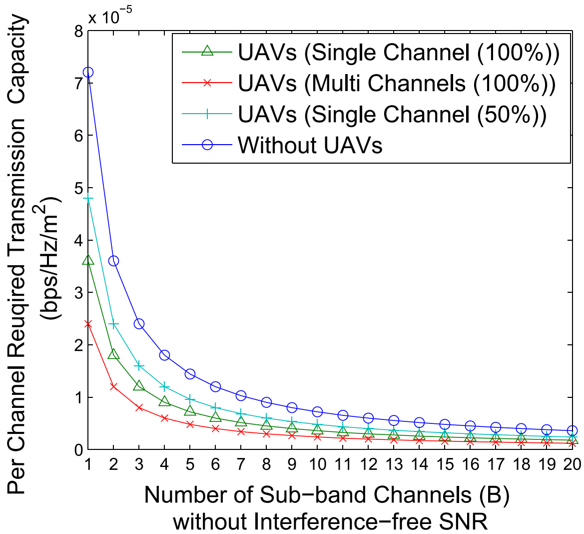

Fig. 13. Per channel required transmission capacity vs. number of sub-band channels (B) without interference-free SNR.

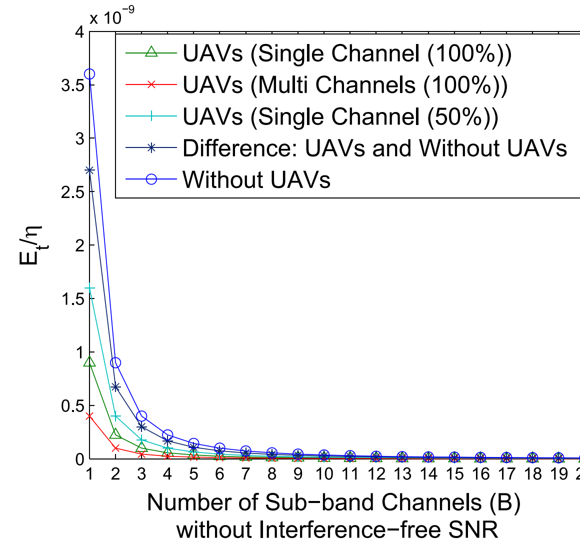

Fig. 15. $\frac{E_t}{\eta}$ vs. number of sub-band channels (B) without interference-free SNR.

shown in Figs. 12 and 13. The results show that without UAVs, a single link has to sustain the required transmission rate, which causes over-utilization of the same link resulting in a decrease in the available energy for a single link; whereas with the deployment of UAVs, the number of alternative links increases, thus, lowering the dependency on a single link for attaining the desired transmission capacity. Further, with more channels per UAV, the dependency of transmission capacity on a single link further reduces to 66.6% with and without the inclusion of interference-free SNR.

5.1.3. Energy asymptote variations

For the networks operating on the crucial aspect of energy consumption, it is required to map the asymptote behavior to analyze the limits up to which an error-free transmission can be attained. This is referred as the Shannon limit and the lowest value is termed as the asymptote. Initially, the asymptote curve for $\frac{E_t}{\eta}$ is observed with and without the interference-free SNR with the increasing number of bands in environments operating with and without UAVs as shown in Figs. 14 and 15. The results comply with the proved Theorem-1 and determine the lower and upper limits for both the graphs. The upper limit is not shown because of its value getting out of the axis bound considered in the graphs to show the effect of UAVs on the 5G-based IoT and BSNs.

With more channels, the energy-asymptote is lowered to a much lower value. This means that UAVs increase the capacity of the network and allow error-free communication at a very low asymptotic value as compared to the network operating without UAVs.

The asymptote for the UAVs-assisted IoT and BSNs is lowered by 75%, which is a sufficient gain to present the utility of UAVs in a network. Further, the difference in the $\frac{E_t}{\eta}$ with respect to spectral efficiency, as shown in Fig. 16, is also between the upper and lower limits as stated in Theorem-1. The numerical analyses presented in this section suggest that the use of UAVs in the 5G-based IoT and BSNs can enhance the capacity of existing architecture to many folds. The proposed approach aims at providing a fault-tolerant and robust connectivity. The fault-tolerance and robustness of the proposed approach are governed by the state cost in Eq. (32).

5.1.4. State cost variations

With an increase in the number of UAVs and the band, the network state cost increases showing more reliable connectivity. Results in Fig. 17 show that an increase in the number of bands impacts more than the increase only in the number of aerial vehicles. The cost is directly related to the probability of connectivity expressed in terms of reliability. Thus, with the increasing number of connections, the

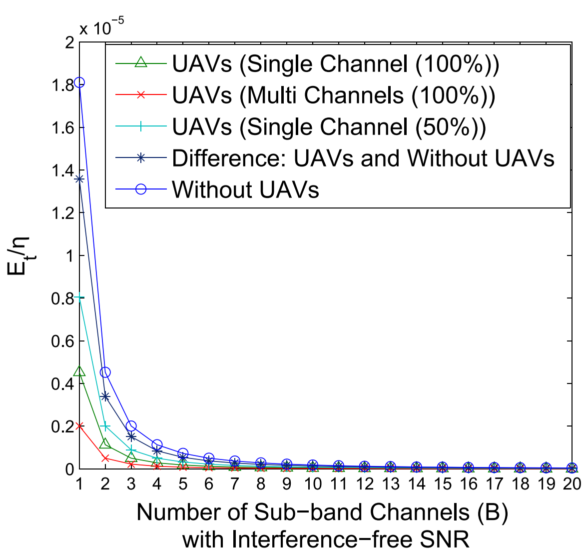

Fig. 14. $\frac{E_t}{\eta}$ vs. number of sub-band channels (B) with interference-free SNR.

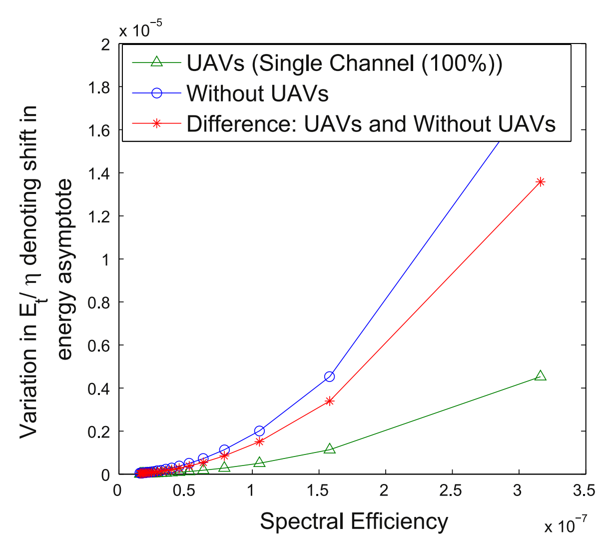

Fig. 16. Variation in $\frac{E_t}{\eta}$ vs. spectral efficiency.

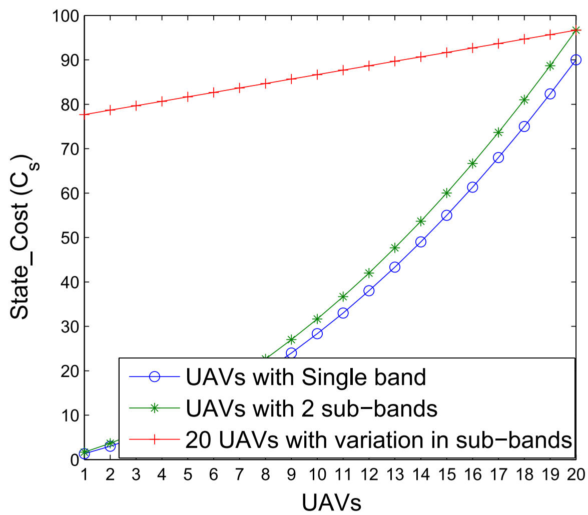

Fig. 17. C_s vs. UAVs.

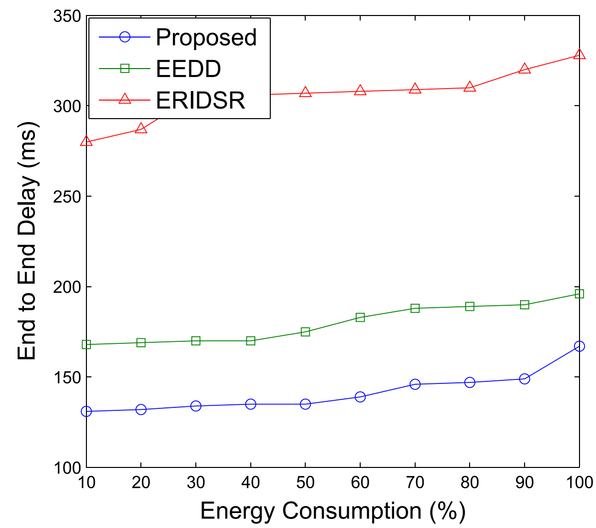

Fig. 18. End to end delay vs. Energy Consumption.

probability of having at least a single connection between every device increases, which in turn increases the overall state cost, thus, resulting in the formation of an efficient network.

5.2. Simulation analyses

The proposed approach was evaluated using the similar parameters as considered for the numerical analyses. A simulation scenario of IoT and BSN was created using *Maltlab*^{TM} and NS-2. The number of devices was kept similar to replicate an actual 5G setup. The traffic and energy model of NS-2 was used to allow a comparison with the existing approaches. The total energy of IoT devices and BSNs was taken as 200 J, with transmission rate between 5 and 55 Kbps. The radio range and distance of transmission for devices varied between 10 and 50 m with transmission energy and processing energy of 0.5 J and 0.25 J, respectively. The traffic type was taken as Constant Bit Rate (CBR). The analyses are presented considering a particular ROI from the entire network with a value of $1000 \times 1000\, m^2$. The number of devices and sensors active in the ROI were 1000, and the number of UAVs available for assistance was 20.

The analyses are presented from the IoT devices and sensors point of view rather than the core network. Also, it is assumed in the simulations that the UAVs are battery operated and the impact of UAVs' battery consumption is not considered since the primary motive of the proposed approach is to enhance the device discovery with preserving the energy of the underlying network. A total of 50 simulation runs was performed to attain the average results for the end to end delay, energy consumption, and packet loss.

For comparative analyses the state-of-the-art approaches for energy-efficient data dissemination in UAVs networks (EEDD) (Sharma et al., 2016c) and ERIDSR (Weng and Lai, 2013) were considered. EEDD is the energy efficient approach for data dissemination in UAV-coordinated sensor networks, whereas ERIDSR is the energy-aware routing for WSNs. Both these approaches focus on the data-dissemination and next hop selection on the basis of energy as one of the key metrics. Thus, based on the similar aspect for energy, both the approaches are considered for comparative analyses with the proposed approach. Apart from the simulation results, the concept in the proposed approach can be evaluated with the existing state-of-the-art solutions presented in Section 2.

5.2.1. End to end delay

The end to end delay is the measure of the network performance considering the transmission, propagation, processing and queuing delays. The latency in the evaluation of the proposed approach for finding the appropriate device is included in the processing delay. With lesser number of devices, the delays are liable to increase. If a network undergoes an increase in the consumption of energy, there are two possibilities for this; one is the operating of all the sensors and devices which consume the maximum amount of energy, another is the wastage of energy if no device is traced by an approach. An increase in the percentage of energy refers to the increase in the number of iterations required to arrive at an optimal decision for selecting the appropriate device. From Fig. 18, it can be noticed that the proposed approach also shows a trend of increase in the iterations leading to the end to end delay during its activity. However, these end to end delays are 21.3% and 53.7% lesser than the EEDD and ERIDSR, respectively. Thus, despite the increase in the energy consumption, the proposed approach is capable of sustaining its connectivity without failure.

5.2.2. Packet loss

In this part, the proposed approach is evaluated for percentage packet loss with an increase in the transmission rate. In order to increase the transmission rate, more processing is performed in the network, which consumes an extra amount of energy. The extra energy is consumed out of the available energy of a node leading to the packet loss in the network. However, unlike end to end delay, where energy is consumed in processing to identify appropriate network device, the packet transmission in the proposed approach is not much affected leading to a low packet loss with the increase in transmission rate. Since more amount of energy is consumed to maintain a link, the packet loss of the network increases. An efficient approach is the one which can deliver packets even at a minimal consumption of energy. The results presented in Fig. 19 show that selection of the optimal rate plays a crucial role in a number of packets lost during transmission. A very high transmission rate may lower the transmission delays but can lead the network into congestion resulting into excessive loss of data. Results show that the proposed approach provides 57.9% and 66% lower packet loss than the EEDD and ERIDSR, respectively. Fig. 19 also shows that for the considered configurations, the packet loss increase linearly up to 35 kbps and any rate lower than this value is enough to sustain the network for longer durations.

5.2.3. Energy consumption

The results were evaluated to analyze the performance of the network in terms of energy consumption per link with an increase in the number of UAVs. A single channel was supported by each UAV in the simulation. As stated in the proposed approach, the UAVs directly account for the extra number of sub-bands which are available to communicate between the two hosts of IoT and BSNs environment.

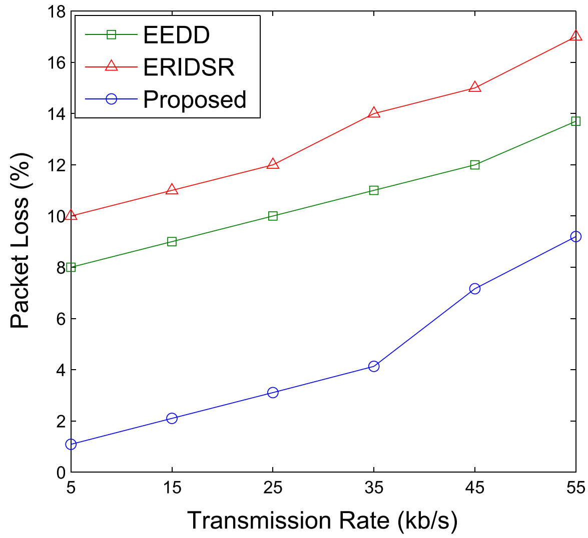

Fig. 19. Packet loss (%) vs. Transmission rate.

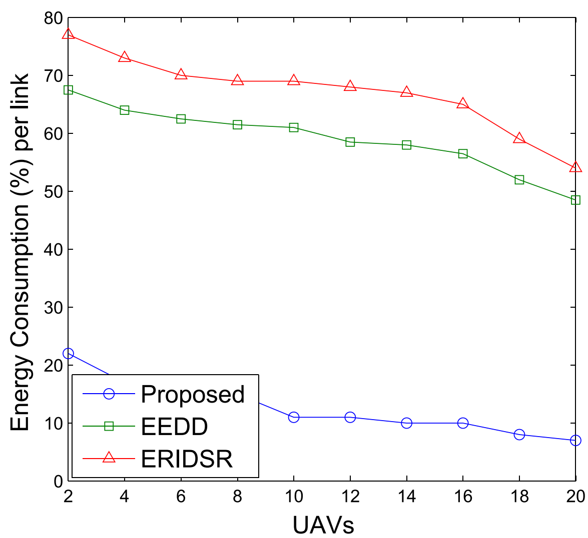

Fig. 20. Energy consumption (%) per link vs. UAVs.

Fig. 20 shows the comparative plot for percentage energy consumption per link with an increase in the number of UAVs. The proposed approach is capable of providing high transmission rate even at the low consumption of energy. The results in the graph show that the proposed approach is capable of reducing the energy consumption to 78.4% and 81% in comparison with EEDD and ERIDSR, respectively.

The results for energy consumption are the actual glimpse of the network lifetime. With less consumption of energy, the lifetime of the network increases and device discovery can be performed efficiently. The proposed approach can be used only for BSNs by altering the communication standard. Thus, from the evaluations presented in this paper, it can be observed that the proposed approach provides better gains for delivery ratio, end to end delays and per link consumption of energy without affecting the capacity of the networks. From the results, it is evident that the proposed approach can handle devices of both IoT and BSNs with a high lifetime.

5.3. Discussions and open issues

The proposed approach is capable of performing energy efficient device discovery in a hybrid environment comprising IoT devices and BSNs. The proposed approach relies on the use of UAVs for multiple sub-bands per channel, which balances computational and energy burden over each channel. The proposed approach provides efficient data offloading by using on-demand small cells in the form of UAVs. With the use of energy charts, the proposed approach is capable of selecting energy-efficient routes. This helps in increasing the overall lifetime of the network. Currently, the proposed approach focuses on fault-tolerance, energy modeling, and traffic modeling to support UAVs in 5G scenarios. The numerical analysis and simulation outcomes justify the performance as well as the impact of the proposed approach. However, there are certain challenges and open issues which can further be considered for advancement in this area of research. These are:

- Formation of drone cloud, along with the management of user load and capacity, is one of the key challenges. UAVs can be used in dense formation to support a large number of users operating in multiple tiers of HetNets.
- Inclusion of mobility laws for UAVs is still a big challenge. Most of the available approaches presented in the related part of this article assume the availability of network support on UAVs. However, the existing solutions should be improved for supporting physical maneuverability of UAVs.
- The architecture with UAVs and IoT needs to be fixed so as to provide a basic underlying support for enhancing other issues related to control and management of UAVs in 5G scenarios.
- Management of BSNs and UAVs on the basis of context is a challenge. How UAVs can be personalized for a particular kind of applications remains an open issue.
- Management of downlink and uplink for low power devices is crucial in UAV networks. This should be taken care of by deploying low-altitude UAVs. The inclusion of radio management solutions and link recovery are the other issues which are yet to be resolved in this area of research.

6. Conclusion

In this paper, an energy efficient approach for device discovery in 5G-based IoT and BSNs using UAVs was presented. The proposed approach utilizes the energy model to formulate the concept of efficient utilization in the upcoming 5G-PPP. A functional architecture was constructed, which utilizes the XML charts to perform device discovery on the basis of network state cost and available energy. The proposed mechanism provides energy model, offloading model and fault-tolerance model to offer a better solution for device discovery in the 5G-based IoT and BSNs.

The numerical results suggest that the UAVs can improve the energy-asymptote of existing networks by 75%. Comparing with existing approaches, the simulations showed that our approach can reduce the energy consumption of the network up to 78.4% with 21.3% reduction in delays without affecting the delivery ratio. Thus, the significant gains achieved in per link energy consumption, end to end delays, packet loss, and enhancement of the network capacity illustrate that the new solution is capable of providing energy efficient device discovery in 5G-based IoT and BSNs using multiple UAVs.

Acknowledgement

The first two authors contributed equally to this work and share the first authorship.

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (2016R1D1A1B03935619). This work was also partly supported by the Soonchunhyang University Research Fund.

References

Akyildiz, I.F., Nie, S., Lin, S.-C., Chandrasekaran, M., 2016. 5g roadmap: 10 key enabling technologies. Comput. Netw. 106, 17–48.
Atzori, L., Iera, A., Morabito, G., 2010. The internet of things: a survey. Comput. Netw. 54 (15), 2787–2805.
Baccelli, E., Hahm, O., Gunes, M., Wahlisch, M., Schmidt, T.C., 2013. Riot os: Towards an os for the internet of things. In: IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), 2013. pp. 79–80.
Bae, C., Stark, W. E., 2007. A tradeoff between energy and bandwidth efficiency in wireless networks. In MILCOM 2007-IEEE Military Communications Conference. pp. 1–7.
Baldus, H., Klabunde, K., Muesch, G., 2004. Reliable set-up of medical body-sensor networks. In: European Workshop on Wireless Sensor Networks. Springer. pp. 353–363.
Bangash, J.I., Khan, A.W., Abdullah, A.H., 2015. Data-centric routing for intra wireless body sensor networks. J. Med. Syst. 39 (9), 1–13.
Bello, O., Zeadally, S., Badra, M., 2016. Network layer inter-operation of device-to-device communication technologies in internet of things (iot). Ad Hoc Netw., 1–11. http://dx.doi.org/10.1016/j.adhoc.2016.06.010.
Borkar, S., Pande, H., 2016. Application of 5g next generation network to internet of things. In: International Conference on Internet of Things and Applications (IOTA) IEEE. pp. 443–447.
Chae, H., Park, J., Song, H., Kim, Y., Jeong, H., 2015. The iot based automate landing system of a drone for the round-the-clock surveillance solution. In: 2015 IEEE International Conference on Advanced Intelligent Mechatronics (AIM). pp. 1575–1580.
Datta, S.K., Bonnet, C., Nikaein, N., 2014. An iot gateway centric architecture to provide novel m2m services. In: IEEE World Forum on Internet of Things (WF-IoT), 2014. pp. 514–519.
Dua, A., Kumar, N., Bawa, S., 2016. Game theoretic approach for real-time data dissemination and offloading in vehicular ad hoc networks. J. Real.-Time Image Process., 1–18.
Dziak, D., Jachimczyk, B., Kulesza, W.J., 2016. Wirelessly interfacing objects and subjects of healthcare system-iot approach. Elektron. Ir Elektrontech. 22 (3), 66–73.
Galov, I.V., Korzun, D., 2014. Fault tolerance support of smart-m3 application on the software infrastructure level. In: Proceedings of the IEEE 16th Conference of Open Innovations Association (FRUCT16). pp. 16–23.
Giang, N.K., Im, J., Kim, D., Jung, M., Kastner, W., 2015. Integrating the epcis and building automation system into the internet of things: a lightweight and interoperable approach. J. Wirel. Mob. Netw. Ubiquitous Comput. Dependable Appl. (JoWUA) 6 (March), 56–73.
Guinard, D., Trifa, V., Karnouskos, S., Spiess, P., Savio, D., 2010. Interacting with the soa-based internet of things: discovery, query, selection, and on-demand provisioning of web services. IEEE Trans. Serv. Comput. 3 (3), 223–235.
H. A. Maior and S. Rao, A self-governing, decentralized, extensible internet of things to share electrical power efficiently. In: IEEE International Conference on Automation Science and Engineering (CASE). pp. 37–43.
Han, B., Srinivasan, A., 2012. ediscovery: Energy efficient device discovery for mobile opportunistic communications. In: Proceedings of the 20th IEEE International Conference on Network Protocols (ICNP). pp. 1–10.
Higginbotham, S., 2011. Ericsson Ceo Predicts 50 Billion Internet Connected Devices by 2020, Ericsson. DOI at: ⟨http://gigaom.com/2010/04/14/ericsson-sees-the-internet-of-things-by-2020⟩.
Ivanovski, D., 2015. The green in internet of things: Case study of faculty environment. In: International Conference on Knowledge Management in Organizations. Springer. pp. 561–571.
Javaid, N., Abbas, Z., Fareed, M., Khan, Z., Alrajeh, N., 2013. M-attempt: a new energy-efficient routing protocol for wireless body area sensor networks. Procedia Comput. Sci. 19, 224–231.
Jiang, D., Zhang, P., Lv, Z., Song, H., Energy-efficient multi-constraint routing algorithm with load balancing for smart city applications. In: IEEE Internet of Things Journal, 3(6), 2016, 1437-47.
Jindal, N., Andrews, J., Weber, S., 2007. Optimizing the Sinr Operating Point of Spatial Networks, arXiv: arXiv:0702030.
Jumira, O., Zeadally, S., 2012. Energy Efficiency in Wireless Networks. ISBN: 978-1-84821-444-6, Wiley-ISTE.
Kandhalu, A., Lakshmanan, K., Rajkumar, R.R., 2010. U-connect: a low-latency energy-efficient asynchronous neighbor discovery protocol. In: Proceedings of the 9th ACM/IEEE International Conference on Information Processing in Sensor Networks. ACM. pp. 350–361.
Kwak, K.S., Ullah, S., Ullah, N., 2010. An overview of ieee 802.15. 6 standard. In: Proceedings of the IEEE 3rd International Symposium on Applied Sciences in Biomedical and Communication Technologies (ISABEL 2010). pp. 1–6.
Lai, X., Liu, Q., Wei, X., Wang, W., Zhou, G., Han, G., 2013. A survey of body sensor networks. Sensors 13 (5), 5406–5447.
Leu, F.-Y., Chen, H.-L., Cheng, C.-C., 2015. Improving multi-path congestion control for event-driven wireless sensor networks by using tdma. J. Internet Serv. Inf. Secur. (JISIS) 5, 1–19.
Li, H., Tan, J., 2010. Heartbeat-driven medium-access control for body sensor networks. IEEE Trans. Inf. Technol. Biomed. 14 (1), 44–51.
Li, C., Song, S., Zhang, J., Letaief, K.B., 2012. Maximizing energy efficiency in wireless networks with a minimum average throughput requirement. In IEEE Wireless Communications and Networking Conference (WCNC). pp. 1130–1134.
Machado, K., Rosário, D., Cerqueira, E., Loureiro, A.A., Neto, A., de Souza, J.N., 2013. A routing protocol based on energy and link quality for internet of things applications. Sensors 13 (2), 1942–1964.
Maskooki, A., Soh, C.B., Gunawan, E., Low, K.S., 2015. Adaptive routing for dynamic on-body wireless sensor networks. IEEE J. Biomed. Health Inform. 19 (2), 549–558.
Merwaday, A., Guvenc, I., 2015. Uav assisted heterogeneous networks for public safety communications. In: Wireless Communications and Networking Conference Workshops (WCNCW). pp. 329–334.
Mozaffari, M., Saad, W., Bennis, M., Debbah, M., 2016. Mobile Internet of Things: Can Uavs Provide an Energy-efficient Mobile Architecture? arXiv: arXiv:1607.02766.
Palattella, M.R., Dohler, M., Grieco, A., Rizzo, G., Torsner, J., Engel, T., Ladid, L., 2016. Internet of things in the 5g era: enablers, architecture, and business models. IEEE J. Sel. Areas Commun. 34 (3), 510–527.
Pandit, S., Sarker, K., Razzaque, M.A., Sarkar, A.J., 2015. An energy-efficient multiconstrained qos aware mac protocol for body sensor networks. Multimed. Tools Appl. 74 (14), 5353–5374.
Park, T., Abuzainab, N., Saad, W., 2016. Learning how to communicate in the internet of things: finite resources and heterogeneity. IEEE Access 4, 7063–7073.
Poon, C.C., Lo, B.P., Yuce, M.R., Alomainy, A., Hao, Y., 2015. Body sensor networks: in the era of big data and beyond. IEEE Rev. Biomed. Eng. 8, 4–16.
Prasad, S.S., Kumar, C., 2012. An energy efficient and reliable internet of things. In: IEEE International Conference on Communication, Information & Computing Technology (ICCICT). pp. 1–4.
Qiu, T., Lv, Y., Xia, F., Chen, N., Wan, J., Tolba, A., 2016. Ergid: an efficient routing protocol for emergency response internet of things. J. Netw. Comput. Appl. 72, 104–112.
Rathore, M.M., Ahmad, A., Paul, A., Rho, S., 2016. Urban planning and building smart cities based on the internet of things using big data analytics. Comput. Netw. 101, 63–80.
Safa, H., Moussa, M., Artail, H., 2014. An energy efficient genetic algorithm based approach for sensor-to-sink binding in multi-sink wireless sensor networks. Wirel. Netw. 20 (2), 177–196.
Shannon, C.E., Weaver, W., 2015. The Mathematical Theory of Communication. University of Illinois Press.
Sharma, V., Kumar, R., Rathore, N., 2015. Topological broadcasting using parameter sensitivity-based logical proximity graphs in coordinated ground-flying ad hoc networks. J. Wirel. Mob. Netw. Ubiquitous Comput. Dependable Appl. (JoWUA) 6 (3), 54–72.
Sharma, V., Bennis, M., Kumar, R., 2016a. Uav-assisted heterogeneous networks for capacity enhancement. IEEE Commun. Lett. 20, 1207–1210.
Sharma, V., Sabatini, R., Ramasamy, S., 2016b. Uavs assisted delay optimization in heterogeneous wireless networks. IEEE Commun. Lett. PP (99), 1.
Sharma, V., You, I., Kumar, R., 2016c. Energy efficient data dissemination in multi-uav coordinated wireless sensor networks. Mob. Inf. Syst., 1–13. http://dx.doi.org/10.1155/2016/8475820.
Sharma, V., You, I., Kumar, R., 2017. Isma: intelligent sensing model for anomalies detection in cross platform osns with a case study on iot. IEEE Access 5, 3284–3301.
Shooman, M.L., 2003. Reliability of computer systems and networks: fault tolerance, analysis, and design. John Wiley & Sons.
Spiess, P., Karnouskos, S., Guinard, D., Savio, D., Baecker, O., De Souza, L.M.S., Trifa, V., 2009. Soa-based integration of the internet of things in enterprise services. In: IEEE International Conference on Web Services, ICWS. pp. 968–975.
Tullberg, H., Li, Z., Hoglund, A., Fertl, P., Gozalvez-Serrano, D., Pawlak, K., Popovski, P., Mange, G., Bulakci, Ö., 2014. Towards the metis 5g concept: First view on horizontal topics concepts. In: IEEE European Conference on n Networks and Communications (EuCNC). pp. 1–5.
Vasilev, A., Paramonov, I., Balandin, S., Dashkova, E., Koucheryavy, Y., 2013. Mechanism for context-aware substitution of smart-m3 agents based on dataflow network model. In: Proceedings of the 5th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT). pp. 113–117.
Weng, C.-E., Lai, T.-W., 2013. An energy-efficient routing algorithm based on relative identification and direction for wireless sensor networks. Wirel. Personal. Commun. 69, 1–16.
Weng, C.-E., Sharma, V., Chen, H.-C., Mao, C.-H., 2016. Peer proximity-based energy-efficient routing algorithm for wireless sensor networks. J. Internet Serv. Inf. Secur. (JISIS) 6 (1), 47–56.
Wu, B.Y., Chao, K.-M., 2004. Spanning Trees and Optimization Problems. CRC Press.
Yoo, S.-J., Park, J.-h., Kim, S.-h., Shrestha, A., 2016. Flying path optimization in uav-assisted iot sensor networks. ICT Express 2 (3), 140–144.
Yu, C., Yao, D., Yang, L.T., Jin, H., 2014. Energy conservation in progressive decentralized single-hop wireless sensor networks for pervasive computing environment. IEEE Syst. J. PP (99), 1–12.
Yu, Y., Lee, S., Lee, J., Cho, K., Park, S., 2016. Design and implementation of wired drone docking system for cost-effective security system in iot environment. In: 2016 IEEE International Conference on Consumer Electronics (ICCE). pp. 369–370.
Z. Peng, T. Kato, H. Takahashi, and T. Kinoshita, 2015. Intelligent home security system using agent-based iot devices. In: IEEE 4th Global Conference on Consumer Electronics (GCCE). pp. 313–314.
Zhou, Z., Yao, B., Xing, R., Shu, L., Bu, S., 2015. E-carp: an energy efficient routing protocol for uwsns in the internet of underwater things. IEEE Sens. J. 16 (11), 4072–4082.
Zhu, R., Zhang, X., Liu, X., Shu, W., Mao, T., Jalaian, B., 2015. Erdt: energy-efficient reliable decision transmission for intelligent cooperative spectrum sensing in industrial iot. IEEE Access 3, 2366–2378.

Vishal Sharma received the Ph.D. and B.Tech. degrees in computer science and engineering from Thapar University (2016) and Punjab Technical University (2012),

respectively. He worked at Thapar University as a Lecturer from Apr'16-Oct'16. Now, he is a post-doctoral researcher in MobiSec Lab. at Department of Information Security Engineering, Soonchunhyang University, Republic of Korea. He is member of various professional bodies and past Chair for ACM Student Chapter-Patiala. His areas of research and interests are 5G networks, UAVs, estimation theory, and artificial intelligence.

Fei Song is with National Engineering Laboratory for Next Generation Internet Technology, School of Electronic and Information Engineering, Beijing Jiaotong University. His current research interests include network architecture, network security, protocols optimization, wireless communications and cloud computing. He also serves as the technical reviewers in several journals including IEEE Transactions on Services Computing, IEEE Transaction on Parallel Distribution System, IEEE Transaction on Emerging Topics in Computing, etc.

Ilsun You [Senior Member] received the M.S. and Ph.D. degrees in computer science from Dankook University, Seoul, Korea, in 1997 and 2002, respectively. He received the second Ph.D. degree from Kyushu University, Japan, in 2012. From 1997–2004, he was at the THINmultimedia Inc., Internet Security Co., Ltd. and Hanjo Engineering Co., Ltd. as a research engineer. Now, he is an associate professor at Department of Information Security Engineering, Soonchunhyang University. He has served or is currently serving as a main organizer of international conferences and workshops such as MobiWorld, MIST, SeCIHD, AsiaARES, and so forth. Dr. YOU is the EiC of Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA). He is in the Editorial Board for Information Sciences (INS), Journal of Network and Computer Applications (JNCA), International Journal of Ad Hoc and Ubiquitous Computing (IJAHUC), Computing and Informatics (CAI), Journal of High Speed Networks (JHSN), Intelligent Automation & Soft Computing (AutoSoft), and Security and Communication Networks (SCN). His main research interests include internet security, authentication, access control, and formal security analysis. He is a Fellow of the IET and a senior member of the IEEE.

Mohammed Atiquzzaman is an Edith Kinney Gaylord Presidential professor in the School of Computer Science at the University of Oklahoma. He teaches courses in Data Networks and Computer Architecture. His research interests are computer networks, Internet protocols over satellite networks, wireless networks and optical communications, image processing and computer vision, non-destructive testing/inspection, multimedia. Many of his current research activities are supported by NSF, NASA and the US Air Force. He serves as the Editor-in-Chief of Journal of Network and Computer Applications, Co-Editor-in-Chief of the Computer Communications Journal and Associate Editor of IEEE Communications Magazine, Journal of Wireless and Optical Communications, International Journal of Communication Systems, International Journal of Sensor Networks, International Journal of Communication Networks and Distributed Systems, and Journal of Real-Time Image Processing.