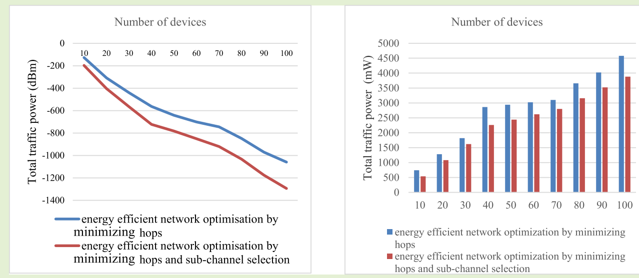
IEEE Sensors Council IEEE SENSORS JOURNAL, VOL. 23, NO. 22, 15 NOVEMBER 2023

Energy-Efficient Traffic in Cloud-Based IoT

Halah Mohammed Al-Kadhim, *Member, IEEE*, and Hamed S. Al-Raweshidy, *Senior Member, IEEE*

***Abstract*—Internet of Things (IoT) is being increasingly used to enable continuous monitoring and sensing of physical things in the world. Energy efficiency is a critical aspect in its design and deployment, as IoT devices are usually battery-powered, and it is difficult, expensive, or even dangerous to replace the batteries in many real physical environments. In this article, an energy-efficient cloud-based IoT network model has been created by optimizing sensor selection, selecting the least number of hops, and leveraging fading sub-channel (sch) gain to reduce traffic power and cancel interference. Using the mixed integer linear programming (MILP), the optimization model and results are determined. The model assesses the outcomes of two possible scenarios: First, network optimization for energy efficiency based on the least number of hops, followed by a comparison with the second scenario. Second, energy-efficient network optimization by minimizing hops and selecting sch. The results indicate that the first scenario consumes more network traffic power in IoT devices, whereas the second scenario reduces network traffic power by an average of 27%.**



***Index Terms*—Cloud computing, energy efficiency, fading channel gain, interference cancellation, Internet of Things (IoT), traffic power, transmission power.**

Nomenclature

Variables

LK_G^d	Variable of end to end link.
R_{jicts}^{DG}	Variable indicator for full path route in physical plan between device and cloud through the repeaters nodes (i, j) where j is a neighbor of i, IoT devices through (c) sub-channel (sch), and time slot (ts).
TF_{cts}^d	Variable indicator for the ON IoT device and its corresponding sub-channel in specified time slot.
H	Variable indicates the number of hops required for the whole path.
ON_d	Variable indicator for transmitting IoT devices.
$TFP(d)$	Variable traffic power of IoT device.
TTP	Variable total traffic power of IoT devices.

Parameters

ts	Parameter of number of time slots.
M	Integer number.
sch	Set of sub-channels.
$NB[i]$	Parameter of the neighbors of the IoT device.
DB_b^d	Parameter of the IoT device building address.
DF_f^d	Parameter of the IoT device floor address.
FG_c^d	Parameter of fading channel gain factor of each sub-channel of each IoT device.
$Noise_d$	Parameter of noise for each IoT device.

Sets

D	Set of IoT devices.
B	Set of buildings.
F	Set of floors.
sch	Set of sub-channels.

I. Introduction

THIS pervasive connection of things will unavoidably give rise to the development of a large amount of data, which will need to be processed, stored, and accessed. However, whereas Internet of Things (IoT) contains a vast number of interconnected devices, these have limited power resources, computation, and storage. Hence, efficient, secure and scalable computing and storage resourcing are necessary [1], [2], [3], [4]. Cloud computing has been recognized in recent years as a template for big data storage and analytics in an efficient approach. Integration of cloud computing and IoT can provide omnipresent sensing services and aggressive processing of detected data [5], [6], [7]. In much research regarding cloud computing-based IoT, the processing has been launched from the IoT devices, such as sensors to the cloud, which symbolizes the data center, however, the idea

Manuscript received 19 September 2023; accepted 7 October 2023. Date of publication 17 October 2023; date of current version 14 November 2023. The associate editor coordinating the review of this article and approving it for publication was Dr. Qammer H. Abbasi. *(Corresponding author: Hamed S. Al-Raweshidy.)*

The authors are with the Department of Electronic and Electrical Engineering, College of Engineering, Design and Physical Sciences, Brunel University London, UB8 3PH Uxbridge, U.K. (e-mail: 1432901@alumni.brunel.ac.uk; hamed.al-raweshidy@brunel.ac.uk).

Digital Object Identifier 10.1109/JSEN.2023.3323805

behind our research is taking the cloud operations that exploit IoT as information resources. That is, the cloud operations could be condensed into data collected from IoT devices. Where, in our model, the cloud should assign the logical tasks, coming from 60 user applications, into a specific IoT device that fit the logical task requirements such as location and function. Our model provides an optimal energy-efficient path between IoT devices and the cloud through hop routes minimization and fading sub-channel (sch) gain utilization. Generally, the highest power consumption is in the radio transmission unit as compared to the other IoT device units (i.e., microcontroller and memory) [8]. Each IoT device has a dual duty as an information router and transmitter. Therefore, smart gadgets are often subject to interference from adjacent devices. Additionally, it increases congestion on the shared frequency of 2.4 GHz which may contribute to the bandwidth restriction [9]. This results in the loss of connections and packet losses, which reduces the quality of the communication channel. Interference considerably reduces the energy transmission efficiency [10], therefore, interference mitigation, would greatly enhance the energy efficiency of the complete network. By employing multichannel communication in wireless networks, interference can be diminished to ensure the network's reliability. The objective of software defined networking (SDN) architecture, assuming SDN in the cloud, is to implement a centralized control server (controller) to enable simple, flexible network programming. SDN utilizes the capability of splitting up the data plane from the control plane in switches and routers (hardware), allowing the control plane to transmit instructions to the data plane [11], [12]. In this article, cloud-based IoT routing is proposed for usage in IoT networks as a promising technology for reducing total traffic power consumption through the following.

1) Developing a mixed integer linear programming (MILP), model to virtualize an IoT network based on the cloud.
2) Selecting routes between IoT devices and the cloud with the fewest number of hops.
3) Minimizing the number of devices that are powered ON.
4) Balance the load through the gateways to prevent traffic congestion in an IoT network.
5) Selecting energy-efficient sch by exploiting sch fading gain.
6) Utilizing the energy-efficient sch time slots.
7) Interference reduction via sch selection.

In this article, two optimization scenarios are implemented. In the first, the model minimizes the traffic power consumption by reducing the number of hops, or repeaters, in the network. In the second case, the model minimizes traffic power consumption by optimizing the selection of fading sch gain and minimizing hops. The achievable performance and comparability between the two scenarios are thoroughly analyzed and discussed.

II. Literature Review

When IoT is widely used to enable continuous monitoring and sensing of the world's physical things. As IoT devices are typically battery-powered, and it can be difficult, expensive, or even dangerous to replace the batteries in many real-world physical environments, energy efficiency is a crucial part of their design and deployment. This article focuses on the approaches that have been used to reduce the power consumption of the cloud-integrated IoT system. These tools allow IoT operators to decrease their energy use. These techniques can maintain the same level of performance with less installation costs.

The subsequent related study focuses on the various approaches that have been presented for minimizing the power consumption of IoT systems and demonstrates the differences between our work and these methodologies.

Studies on the energy efficiency of IoT devices that combine cloud computing. In [13], smart devices with several radio links determine heuristically the optimal link to transmit data to the cloud based on the link's quality and energy cost. Kaur and Sood [14] propose an energy-efficient architecture for IoT. This architecture enables the system to estimate the sleep interval of sensors. The anticipated value can be used to increase cloud resource utilization. Lim et al. [15] discuss a system-on-chip hardware architecture with a lower energy consumption that targets digital block design. They presented Torpor, a power-aware hardware scheduler, in this study [16]. Pan et al. [17], formulate an IoT framework with intelligent location-based automated and networked energy control. Kim [18] proposes a polynomial-time approach for the energy-efficient downloading of packets from medical cloud storage to medical IoT devices. Perera et al. [19] offer location- and activity-aware mobile sensing platform for the IoT called the context-aware mobile sensor data engine. They present a novel media access control technique, Sun and Ryoo [20] by lowering the energy consumption of smart sensors based on buffer threshold values that are preconfigured based on distances from the sink node. They introduced a virtual cluster head election technique in [21], that provides an energy-efficient clustering algorithm and examines CH distribution in wireless sensor network (WSN). In this study, their primary contributions consist of cloud-based services for monitoring the tradeoff between the data quality (DQ) and energy consumption of the sensor, an architecture that adapts to DQ requirements, and a producer/consumer data stream that is most compatible with the cloud service. In this study [22], a middle layer called an edge computing layer is introduced to reduce latency in IoT. They wanted to reduce the energy consumption of a mobile device in addition to the cloud system while meeting a task's deadline. Dinh and Kim [23] provide an effective interactive paradigm for sensor-cloud integration that allows the sensor-cloud to give sensing services on-demand to several applications with varying latency needs. Mekala and Viswanathan [24], present an optimum energy-efficient method for selecting and migrating virtual machines for IoT in the cloud environment. Xu et al. [25], emphasize how to increase the energy efficiency of edge caching by storing and processing data in memory. Al-Turjman [26] suggest a cognitive data delivery (routing) protocol that overcomes the difficulties associated with data delivery in IoT networks constituted of energy-constrained IoT sensors.

When selecting the next hop for routed packets in the targeted WSN, they take the total network energy into account. A low-power, energy-efficient communication protocol is suggested in the publication [27], The presented protocol optimizes the manner in which environmental data is obtained, packed, and transferred over vast distances with minimal energy use. The model suggested in [28] combines the prediction technique in the cloud system with a load balancing routing approach in a sensor network to reduce energy usage. In reference to flow scheduling between edge and cloud devices, they present in [29], a SDN-based edge-cloud interaction. Wherein SDN provides effective support for middleware. They analyze the suggested strategy in terms of two optimization problems: tradeoffs between energy efficiency and latency and energy efficiency and bandwidth. Energy consumption of nano data centers (nDCs) for the IoT was explored in [30], where flow- and time-based models of energy usage for shared and nonshared network equipment have been presented and utilized, respectively. They compared the energy consumption of cloud computing programs using centralized data centers to those employing nDCs in fog computing.

1) The aforementioned works involve concentrating on how to maximize energy efficiency and the quality of service via cloud computing using different schemes while ignoring the distribution of the demands on the IoT network that have been generated by cloud platforms as in our proposed architecture in this article. This is done using location and function criteria of the nodes.
   In addition, some works have tackled the issue of energy-efficient routing in IoT networks. Frey et al. [31] presented an energy-aware ant routing algorithm (ARA) for IoT. They delivered new techniques for estimating the viability of a path and energy information dissemination. Javaid et al. [32] propose two new routing methods for underwater WSN. The offered techniques considerably enhance the network's delivery ratio, energy consumption, and delay. Kumbhar and Chavan [33] introduce a technique for energy-efficient ring routing in WSN with a mobile sink. This protocol employs a hierarchical architecture that minimizes the network's energy usage. Preethi et al. [34] describe a modified balanced energy efficient network integrated super heterogeneous strategy, for cluster head selection. Zhang et al. [35] classify industrial sensed data into three categories and propose an energy-efficient and QoS-aware routing algorithm. Each type of data packet was routed using a distinct routing strategy. In this research [36], the QoS routing of WSN is examined. To satisfy QoS criteria for packet routing in WSNs, they suggest a solution based on a distributed learning automaton. Regarding energy efficiency, their technique was to choose the best viable nodes for conserving the residual energies of other nodes.
2) Although numerous techniques for hops minimization were offered in these studies in order to improve energy efficiency, none of these contributions considered additional transmission power reduction of the network based on fading sch gain.
   Utilizing channel state information to achieve energy efficiency has been the subject of some research. Ren et al. [37] examine the dynamic channel accessing problem in order to increase the energy efficiency of clustered cognitive radio sensor networks. Digital and analog transmission energy planning techniques for progressive estimation in multihop sensor networks were introduced in [38]. Wu et al. [39], develop an optimization problem to address the imbalanced energy consumption issue in the orthogonal frequency division multiplexing (OFDM) system for a WSN. Li et al. [40] examine a computation offloading management challenge for IoT in a heterogeneous network, including information about diverse processing resources, latency needs, power consumption at end devices, and channel statuses. Wang et al. [41] present an analytical model of the energy transmission channel for the resonant beam charging (RBC) system and investigate how far RBC can travel and how much power it can theoretically convey. As in article [42], several works have evolved a multichannel technique to address the interference problem. They investigate the effect of adjacent channel interference (ACI) on WLANs in IoT networks and formulate an interference-aware self-optimizing (IASO) Wi-Fi architecture with multichannel multilevel carrier sensing and adaptive initial gain control. In this study [43], a logical link-based partially overlapping channels interference model is analyzed to diminish inter-channel interference, and a channel selection mechanism is established.
3) However, the aforementioned works have concentrated on utilizing sch techniques and channel state information either for interference cancellation or energy efficiency, and have therefore not taken advantage of them to simultaneously lower traffic power and interference, as proposed in our work.
4) Overall, in related research, despite the fact that several techniques were offered to accomplish energy efficiency or interference cancellation in a cloud-based IoT network, none of the contributions considered integrating these schemes to achieve both objectives and with using MILP to achieve optimal solution. In contrast to previous methodologies, in our work, cloud technology and our proposed network architecture were employed for hops minimization and fading sch gain selection optimization, to realize energy efficiency and interference elimination simultaneously employing the MILP programming tool.

III. CLOUD-BASED IoT SYSTEM

In this article, it is assumed that there is a real-world scenario, such as smart buildings in a smart city with several cloud-based applications [44], [45], which are performing in the cloud and requiring data collection such as temperature sensing of the surrounding environment. Sensors in IoT devices collect the data, with the devices having specific characteristics and being connected to the cloud via gateways. Physically, the devices layer has a vast number

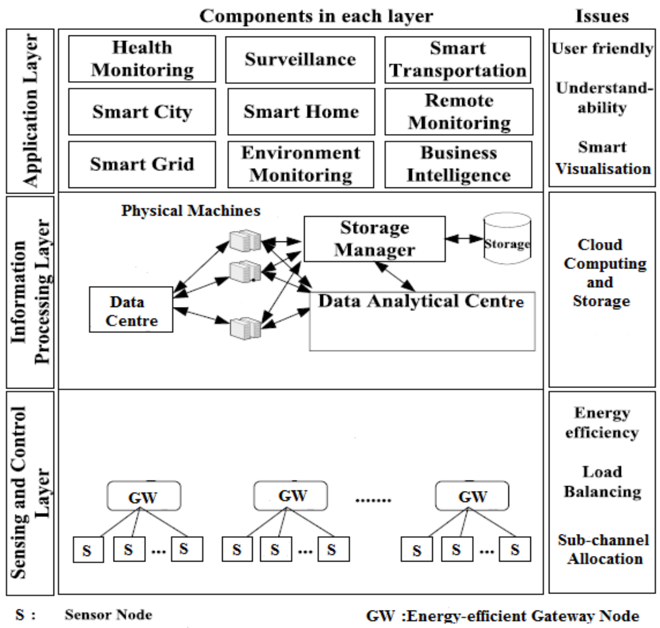


Fig. 1. Proposed architecture of cloud-based IoT.

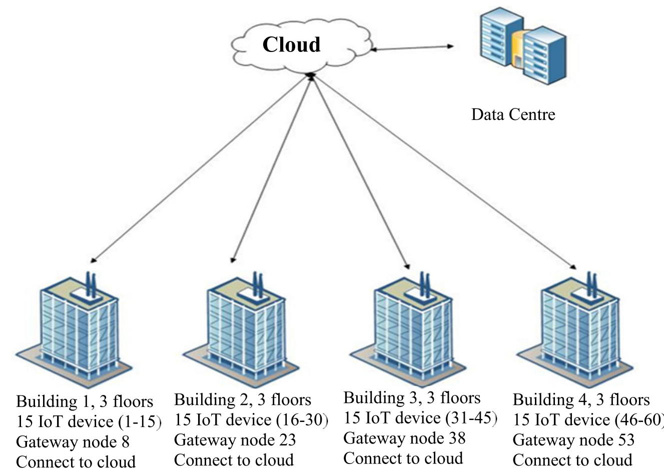


Fig. 2. Physical network of a smart city.

of IoT devices that are distributed arbitrarily based on their sensing and location capabilities. Moreover, each IoT device continuously transmits its collected data to the cloud, which has the computational function of analyzing and utilizing these data in accordance with their applications. In other words, cloud computing provides a platform as a service (PaaS) for users to run, administer, and evolve their applications. These applications rely on the information that needs to be collected from IoT devices, such as an application demand for real-time information, for example, temperature or humidity in a specific area of the city. The application layer will pass this demand to the cloud, which will then evaluate and process it before sending the results back to the application layer. To accomplish this, the cloud will request this data from the IoT devices allocated in the area concerned and then collect information through the gateways connected to it.

Our model's proposed architecture is depicted in Fig. 1 and consists of three layers [14]: 1) sensing and control layer—this layer is comprised of low-powered sensors, actuators, and gateways. (It collects and transmits data for analysis.); 2) information processing layer—the data gathered by the sensors are in unprocessed form and in vast quantities; to extract interpretable information from these data, they must be stored, processed, and analyzed. Using the cloud computing platform to provide storage and analytical data tools, this layer performs these tasks; it consists of a data analytics center, storage media, and other physical machines; and 3) application layer—this layer is responsible for visualizing the processed data and presenting them to the users in an inventive and easily understandable format. It provides an interface for applications such as health monitoring, intelligent transportation, and environmental monitoring in order to provide services to end users.

Due to the fact that the real world (IoT network) is connected to the cloud and both have distinct communication protocols, data is delivered to the cloud via a gateway.

IV. Network Optimization Model of Cloud-Based IoT

Our mathematical model is developed using MILP, a form of mathematical programming that can optimize a function with several variables and restrictions. As stated previously, a cloud-based IoT system is assumed. As depicted in Fig. 2, the IoT devices are distributed in one physical grid, in this example smart buildings, consisting of 60 IoT devices connected via a physical network and distributed across four buildings. It is assumed that each of these smart buildings (B) has three floors (F) with five IoT devices, for a total of 15 IoT devices per building. As depicted in Fig. 3, the central node on the second floor of each building acts as a gateway for collecting data to send to or receive from the cloud. Each IoT device is connected to its neighbors via a physical plan, and the floors are connected by the central nodes on each floor. So that the logical tasks will be allocated by the cloud according to the task's required function (sensing), the address of the floor and building, into the corresponding IoT device that matches the task's requirements. In addition to the ability to process, store, and function, each IoT device possesses two of the following functions: alarm, security, climate, and/or entertainment. As depicted in Fig. 3, the IoT network topology employed here is a star, in which each sensor node communicates with its neighbor and can relay messages from that neighbor throughout the network [46].

The model considers that each IoT device is connected to variant sensors (S) with particular specifications, which are the functionality of each node and location. The MILP model will optimize the path selection between IoT devices and the cloud in an energy-efficient manner by minimizing total power consumption and optimizing the network. This signifies that the model determines the optimal IoT device and optimal fading sch gain for each logical node, based on the capabilities of the IoT device, with minimal traffic power consumption and an energy-efficient network path.

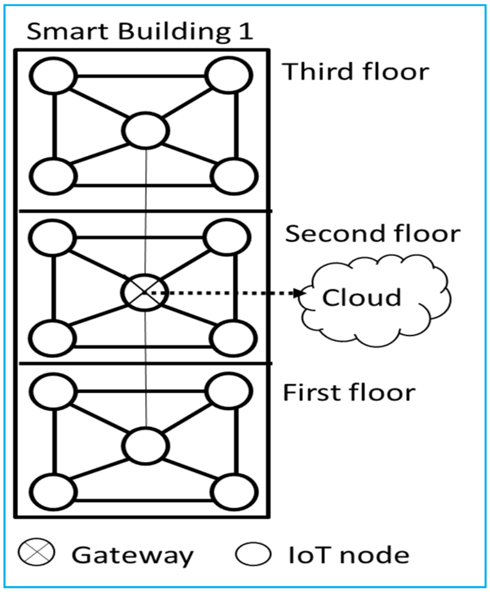


Fig. 3. Topology of one of the smart buildings in the proposed IoT network of a smart city.

V. Objectives of the Proposed Model

A. Minimizing the Number of Hops

The routing concept in this article is based on the flow conservation constraint for the traffic flows in the physical network by Shen and Tucker [47].

A parameter LK_G^d indicating the traffic (link) between the IoT device (d) and the cloud is established (G)

$$\mathrm{LK}_G^d = \begin{cases} 1, & \text{If there is link between the IoT Device and the Cloud} \\ 0, & \text{Else.} \end{cases} \quad (1)$$

A binary variable $R_{i\,j\,c\,ts}^{d\,G}$ is created to represent the route between the IoT device (d) and the cloud

$\forall d, i \in D, d \neq G$

$$\left\{ \sum_{j\in D, i\neq j} \sum_{c\in \mathrm{sch}} \sum_{ts\in T} R_{i\,j\,c\,ts}^{d\,G} - \sum_{j\in D, i\neq j} \sum_{c\in \mathrm{sch}} \sum_{ts\in T} R_{j\,i\,c\,ts}^{d\,G} \right\} = \mathrm{LK}_G^d \quad (2)$$

$$\left\{ \sum_{j\in D, i\neq j} \sum_{c\in \mathrm{sch}} \sum_{ts\in T} R_{i\,j\,c\,ts}^{d\,G} - \sum_{j\in D, i\neq j} \sum_{c\in \mathrm{sch}} \sum_{ts\in T} R_{j\,i\,c\,ts}^{d\,G} \right\} = 0 \quad (3)$$

$$\left\{ \sum_{j\in D, i\neq j} \sum_{c\in \mathrm{sch}} \sum_{ts\in T} R_{i\,j\,c\,ts}^{d G} - \sum_{j\in D, i\neq j} \sum_{c\in \mathrm{sch}} \sum_{ts\in T} R_{j\,i\,c\,ts}^{d\,G} \right\} = -\mathrm{LK}_G^d. \quad (4)$$

Flow conservation restriction has three options, as depicted in Fig. 4 and in (2)–(4). It claims that a node is neither a source nor a destination if the traffic entering and leaving it is identical. If the traffic leaving the node minus the traffic entering the node matches the demand originating in the node, then the node is a source. It is a destination if the amount of traffic arriving minus the amount of traffic departing is equal to the amount of demand meant for it.

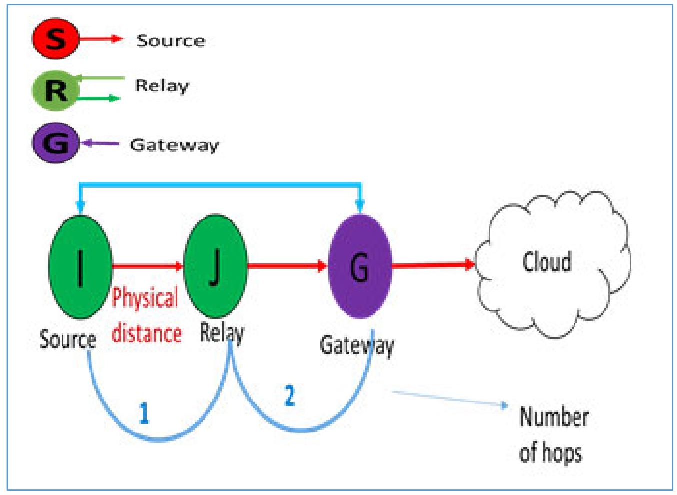


Fig. 4. Routing between an IoT device and the cloud in the physical network.

The model optimizes network paths by selecting the route with the minimum number of hops (H), with H being the objective function.

Objective: Minimize

$$\sum_{\substack{d\in D,\\ d\neq G}} \sum_{i\in D} \sum_{j\in D, i\neq j} \sum_{c\in \mathrm{sch}} \sum_{ts\in T} R_{i\,j\,c\,ts}^{d\,G} = H \quad (5)$$

where H is variable, D is the set of IoT devices, T is the set of time slots, sch is the set of sch.

$R_{i\,j\,c\,ts}^{d\,G}$ is a binary variable that represents the route between the IoT device d and the cloud G through the repeater nodes, where j is the neighbor of i, through c sch, and time slot ts.

In Nomenclature section, the variables, parameters, and sets described by the MILP model are outlined briefly.

B. Interference Cancellation

To eliminate interference, the following three constraints have been implemented.

First, there is a single traffic path between the device and the cloud

$$\sum_{j\in D, i\neq j} \sum_{c\in \mathrm{sch}} \sum_{ts\in T} R_{i\,j\,c\,ts}^{d\,G} \leq 1 \quad \forall d \in D\ \forall i \in D, d \neq G. \quad (6)$$

As an indicator for the power ON device and the corresponding selected sch and time slot, the binary variable $\mathrm{TF}_{c\,ts}^d$ is created

$$\mathrm{TF}_{cts}^d * M \geq \sum_{j\in NB[i], i\neq j} \sum_{ts\in T} \sum_{d\in D, d\neq G} R_{i\,j\,c\,ts}^{d\,G} \quad (7)$$

$$\mathrm{TF}_{c\,ts}^d \leq \sum_{ts\in T} \sum_{j\in NB[i], i\neq j} \sum_{d\in D, d\neq G} R_{i\,j\,c\,ts}^{d\,G}$$

$$\forall i \in D, c \in \mathrm{sch},\ M\text{: integer number.} \quad (8)$$

Second, in order to prevent transmission duplication, each IoT device must use either a single sch or none for each transmission

$$\sum_{ts\in T} \sum_{c\in sch} \mathrm{DB}_b^d\ \mathrm{DF}_f^d \mathrm{TF}_{c\,ts}^d \leq 1 \quad \forall d \in D\ \forall b \in B\ \forall f \in F \quad (9)$$

TABLE I
CC3200 SimpleLink Wi-Fi Parameters

Parameter	Value
TX Power	14.5 dBm
RX Power	–74.0 dBm
V (battery)	2.1 to 3.6 V
RX Traffic	59 mA
TX Traffic	229 mA

where DB_b^d is the building address of IoT device, and DF_f^d is its floor address.

The third restriction is that each floor has a specific number of sch, and the number of devices using a sch cannot exceed the number of time slots allocated to that sch. This will prevent interference

$$\sum_{ts\in T}\sum_{d\in D}\mathrm{DB}_b^d\mathrm{DF}_f^d\mathrm{TF}_{c\,ts}^d \le \sum_{ts\in T} ts \quad \forall b\in B\ \forall f\in F\ \forall c\in sch. \tag{10}$$

C. Maximizing Fading Channel Gain

The following restrictions evaluate each device's transmitted (traffic) power in dBm. The objective of the model is to minimize $\mathrm{TFP}(d)$, hence picking the fading channel with the maximum gain.

Objective: Minimize

$$-74 * \mathrm{ON}_d - \sum_{c\in sch}\sum_{ts\in T}\mathrm{TF}_{c\,ts}^d * \mathrm{FG}_c^d + \mathrm{ON}_d{*}\mathrm{Noise}_d = \mathrm{TFP}(d) \quad \forall d\in D \tag{11}$$

where (11) is derived from the following fading channel equation:

$$Y = HX + N \tag{12}$$

where X: represents the transmitted signal, Y: represents received signal, H: represents the fading channel gain, and N: denotes a zero-mean Gaussian random variable with variance σ^2 [48]. Equation (12) which in dBm refers to

$$\begin{aligned} Y &= H + X + (-N)\\ X &= Y - H + N. \end{aligned} \tag{13}$$

Equation (13) is equivalent to (11) where, (FG_c^d) represents the fading sch gain factor for the c sch for device d, (Noise_d) represents the noise for each IoT device and (ON_d)represents the transmitting devices. As described in Table I, the average receiver sensitivity is -74. In such a method, a minimum transmitted power level is specified to control interference, enabling the QoS of IoT application users to be assured due to the low interference strength of IoT device transmitters.

The subsequent restriction evaluates the overall transmitted power.

Objective: Minimize

$$\sum_{d\in D}\mathrm{TFP}(d) = \mathrm{TTP}. \tag{14}$$

TABLE II
Model Parameters

Parameter	Value
Noise range	-20 to -50 dBm
Fading channel gain factor	0 to 25 dB

Finally, the model optimizes the entire network traffic power consumption by minimizing total traffic power and hop count.

VI. Performance Evaluation

In order to evaluate the performance of the model, it has been run for two scenarios of optimization. The first involves reducing the number of hops only, whilst for the second, the hops are reduced and optimal selecting of the highest fading sch gain is deployed. We have three metrics to compare the two scenarios (Number of hops, sch, and time slot selection), these metrics effects can be shown in the total traffic consumption of the network. Meaningfullly, first scenario includes no constraint for the number of hops, using any available sch (random selection) and utilizing any available time slot for the randomly selected channels, while the second optimized scenario includes the minimum number of hops, optimal selection of high gain sch and utilization of the time slots of these high gain sch.

The model has been run for up to request multidevices simultaneously. The power parameters of an IoT device is as mentioned on the data sheet of CC3200 SimpleLink Wi-Fi [49]. Furthermore, CC3200 supports most Arduino compatible shields [50]. Table I displays the features of CC3200 which has 802.11 b/g/n Radio, TX power: 14.5 dBm (as maximum transmitted power), RX sensitivity: -74.0 dBm.

The values of model parameters are based on [51] and are summarized in Table II. A Rayleigh fading channel is assumed since Rayleigh distribution best describes the envelope of a fading signal [48].

Fig. 5 displays the total traffic power in dBm of our model versus the variant percentage of the number of IoT devices that generate traffic. In Fig. 5(a), the model minimizes the number of hops by the selection of the shortest path between the device and the cloud, according to the constraints. In addition, the model also minimizes the power consumption by link utilization.

Also, Fig. 5(b), displays the second scenario of energy-efficient network optimization for the same number of devices and physical network, with the objective of additional traffic power minimization. By minimizing the number of hops of the routes and the traffic power by selecting the highest fading sch gain, and by utilizing the time slots of the energy efficient sch according to (11), this can be achieved. Fig. 6 reveals that the average power saving in the second scenario of energy-efficient network optimization is about 27.44%. This saving results from the optimal selection of high gain sch, to which the random sch selection and utilization of the time slots of these sch in the first scenario is inferior.

The results have been displayed in dBm as the channel gain obtained by reflecting from a wall or other reflectors can be

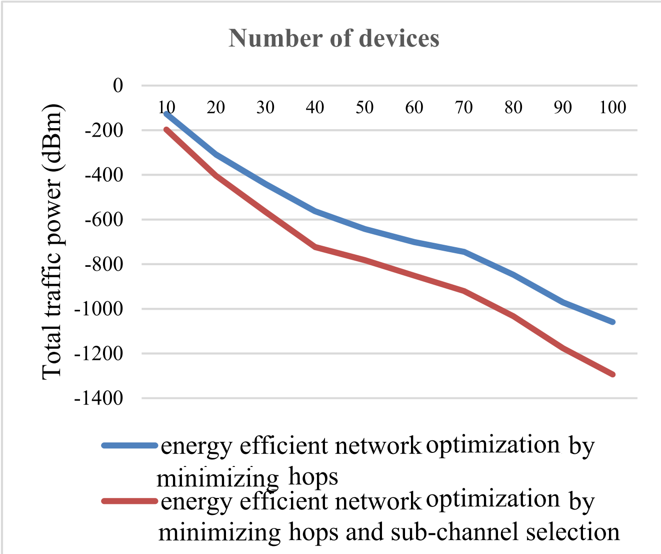


Fig. 5. Total traffic power in dBm of different numbers of devices for (a) energy efficient network optimization by minimizing hops and (b) energy efficient network optimization by minimizing hops and sch selection.

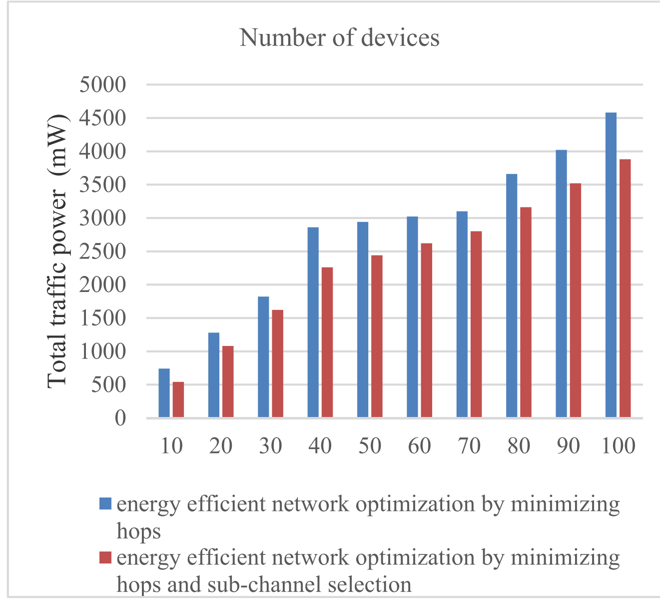


Fig. 6. Total traffic power in mW of different number of devices for (a) energy efficient network optimization by minimizing hops and (b) energy efficient network optimization by minimizing hops and sch selection.

measured with this unit and there is no source like an amplifier to produce power in watts. Hence, to display the transmitted power in mW, the conversion approach has been used between the traffic power in the device circuit, which is measured in mW (since it is produced from a power amplifier) and between the radiated power in the air that is measured in dBm. Table III displays the mapping approach followed in this work as below:

TABLE III
MAPPING APPROACH

Power in dBm	Power in mW
-40 or less	180
-30	280
-20	380
-10	480
0	580
+14	680

Where these values are considered from [24] and Table I. Maximum transmitted power in mW (2.9 V $*$ 229 mA $=$ 680 mW) corresponds to the maximum transmitted power in dBm (14 dBm). While the minimum transmitted power in mW (3 V $*$ 59 mA $=$ 180 mW) corresponds to the minimum transmitted power in dBm (-40 dBm).

Fig. 6 displays the model results of total traffic power in mW for energy-efficient network optimization by minimizing hops and compares this with the total traffic power of energy-efficient network optimization by minimizing hops and sch selection for the same number of devices. The total traffic power is represented in (14). From the results, it is concluded that energy-efficient network optimization just by minimizing hops consumes more traffic power in IoT devices than when sch selection is included for the same number of devices. That is, optimal high gain sch selection in the second scenario, which is excluded from the first, results in greater network energy efficiency.

In terms of figures, in the second scenario, there is a higher power saving of 27% in the case of 10% of IoT devices, because the logical plan required for this case is a small network of IoT devices, and the model can select the optimal sch, because their number is low. While the same model's results show lower power saving when there are 70% IoT devices of only 9.6%, because of the increasing traffic demands of multiple ones. Where the model has to use the available nonoptimal sch as the IoT devices increase. Furthermore, IoT device's distribution is nonhomogenous (in reality), which means that the allocated IoT devices could be far away from the gateway, and that will require a high number of hops needing high traffic power.

VII. Conclusion

This article deals with the aspect of traffic power consumption minimization, furthermore, the routing of cloud-based IoT is suggested to be used in the IoT networks as a promising technology to minimize the total traffic power consumption as follows: selecting the minimum number of hops between IoT devices and cloud, selecting energy efficient sch by exploiting fading gain, utilizing time slots of the energy efficient sch, reducing interference through sch selection. The model evaluates the results for two scenarios of optimization: 1) reducing the number of hops and 2) reducing the number of hops and selecting the highest fading channel gain. The results show that the second proposed scheme has an energy saving of 27% by minimizing hops and sch selection when compared to just minimizing the hops, as in the first scenario put forward.

VIII. Future Work

Intelligence in IoT networks is suggested for future work. In this article, the computing process is centralized in the cloud; therefore, as future work, deploying fog computing is a decentralized computing infrastructure in which data, computing, storage, and applications are located somewhere between the data source and the cloud. Using fog computing for data processing requires the IoT network to be intelligent, thus making decisions for sending the collected data to the cloud or for fog computing. Artificial intelligence (AI) simulates intelligent behavior in machines of all kinds; the model will compute how much power has been consumed and saved for each case.

Additionally, splitting the data traffic over two or more nodes is recommended to avoid link overhead, packet drop, and latency. The nodes will be nominated according to the available traffic and the link capacity limits. The total traffic power consumption results of two schemes, the distributed and nondistributed traffic schemes, will be compared.

Finally, as experimental validation would strengthen the findings and demonstrate the practicality of the approach, it is suggested to deploy the proposed work into a practical application. For example, using sensors in a manufactory, these sensors are connected to the cloud and monitoring utility to reduce power consumption. The simulation results (depending on datasheets) should be compared with testbed results that depend on the hardware used to implement the experiment.

References

[1] H. M. Al-Kadhim and H. S. Al-Raweshidy, "Energy efficient data compression in cloud based IoT," *IEEE Sensors J.*, vol. 21, no. 10, pp. 12212–12219, May 2021.

[2] Y. Zhao, P. Deng, J. Liu, M. Wang, and J. Wan, "LCANet: Lightweight context-aware attention networks for earthquake detection and phase-picking on IoT edge devices," *IEEE Syst. J.*, vol. 16, no. 3, pp. 4024–4035, Sep. 2022.

[3] H. Wei, H. Luo, Y. Sun, and M. S. Obaidat, "Cache-aware computation offloading in IoT systems," *IEEE Syst. J.*, vol. 14, no. 1, pp. 61–72, Mar. 2020.

[4] F. Yang et al., "Internet-of-Things-enabled data fusion method for sleep healthcare applications," *IEEE Internet Things J.*, vol. 8, no. 21, pp. 15892–15905, Nov. 2021.

[5] H. M. Al-Kadhim and H. S. Al-Raweshidy, "Energy efficient and reliable transport of data in cloud-based IoT," *IEEE Access*, vol. 7, pp. 64641–64650, 2019.

[6] H. Kaur and S. K. Sood, "Energy-efficient IoT-fog-cloud architectural paradigm for real-time wildfire prediction and forecasting," *IEEE Syst. J.*, vol. 14, no. 2, pp. 2003–2011, Jun. 2020.

[7] N. H. Thanh, N. Trung Kien, N. V. Hoa, T. T. Huong, F. Wamser, and T. Hossfeld, "Energy-aware service function chain embedding in edge–cloud environments for IoT applications," *IEEE Internet Things J.*, vol. 8, no. 17, pp. 13465–13486, Sep. 2021.

[8] Y. Liang and Y. Li, "An efficient and robust data compression algorithm in wireless sensor networks," *IEEE Commun. Lett.*, vol. 18, no. 3, pp. 439–442, Mar. 2014.

[9] L. Farhan, O. Kaiwartya, L. Alzubaidi, W. Gheth, E. Dimla, and R. Kharel, "Toward interference aware IoT framework: Energy and geo-location-based-modeling," *IEEE Access*, vol. 7, pp. 56617–56630, 2019.

[10] L. Li, Y. Xu, Z. Zhang, J. Yin, W. Chen, and Z. Han, "A prediction-based charging policy and interference mitigation approach in the wireless powered Internet of Things," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 2, pp. 439–451, Feb. 2019.

[11] A. Voellmy and J. Wang, "Scalable software defined network controllers," in *Proc. ACM SIGCOMM Conf. Appl., Technol., Archit., Protocols Comput. Commun.*, Aug. 2012, vol. 42, no. 4, pp. 289–290.

[12] F. Hu, Q. Hao, and K. Bao, "A survey on software-defined network and OpenFlow: From concept to implementation," *IEEE Commun. Surveys Tuts.*, vol. 16, no. 4, pp. 2181–2206, 4th Quart., 2014.

[13] K. Dhondge, R. Shorey, and J. Tew, "HOLA: Heuristic and opportunistic link selection algorithm for energy efficiency in Industrial Internet of Things (IIoT) systems," in *Proc. 8th Int. Conf. Commun. Syst. Netw. (COMSNETS)*, Bangalore, India, Jan. 2016, pp. 1–6.

[14] N. Kaur and S. K. Sood, "An energy-efficient architecture for the Internet of Things (IoT)," *IEEE Syst. J.*, vol. 11, no. 2, pp. 796–805, Jun. 2017.

[15] Y. W. Lim, S. B. Daas, S. J. Hashim, R. M. Sidek, N. A. Kamsani, and F. Z. Rokhani, "Reduced hardware architecture for energy-efficient IoT healthcare sensor nodes," in *Proc. IEEE Int. Circuits Syst. Symp. (ICSyS)*, Langkawi, Malaysia, Sep. 2015, pp. 90–95.

[16] P. Anagnostou et al., "Energy and power awareness in hardware schedulers for energy harvesting IoT SoCs," *Integr., VLSI J.*, vol. 67, pp. 33–43, Jul. 2019.

[17] J. Pan, R. Jain, S. Paul, T. Vu, A. Saifullah, and M. Sha, "An Internet of Things framework for smart energy in buildings: Designs, prototype, and experiments," *IEEE Internet Things J.*, vol. 2, no. 6, pp. 527–537, Dec. 2015.

[18] J. Kim, "Energy-efficient dynamic packet downloading for medical IoT platforms," *IEEE Trans. Ind. Informat.*, vol. 11, no. 6, pp. 1653–1659, Dec. 2015.

[19] C. Perera, D. S. Talagala, C. H. Liu, and J. C. Estrella, "Energy-efficient location and activity-aware on-demand mobile distributed sensing platform for sensing as a service in IoT clouds," *IEEE Trans. Computat. Social Syst.*, vol. 2, no. 4, pp. 171–181, Dec. 2015.

[20] K. Sun and I. Ryoo, "A study on medium access control scheme for energy efficiency in wireless smart sensor networks," in *Proc. Int. Conf. Inf. Commun. Technol. Converg. (ICTC)*, Oct. 2015, pp. 623–625.

[21] M.-Y. Tsai and Y.-C. Chen, "A virtual cluster head election scheme for energy-efficient routing in wireless sensor networks," in *Proc. 3rd Int. Conf. Future Internet Things Cloud*, Aug. 2015, pp. 341–348.

[22] S. K. Mishra, D. Puthal, B. Sahoo, S. Sharma, Z. Xue, and A. Y. Zomaya, "Energy-efficient deployment of edge dataenters for mobile clouds in sustainable IoT," *IEEE Access*, vol. 6, pp. 56587–56597, 2018.

[23] T. Dinh and Y. Kim, "An efficient sensor-cloud interactive model for on-demand latency requirement guarantee," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Paris, France, May 2017, pp. 1–6.

[24] M. S. Mekala and P. Viswanathan, "Energy-efficient virtual machine selection based on resource ranking and utilization factor approach in cloud computing for IoT," *Comput. Electr. Eng.*, vol. 73, pp. 227–244, Jan. 2019.

[25] J. Xu, K. Ota, and M. Dong, "Saving energy on the edge: in-memory caching for multi-tier heterogeneous networks," *IEEE Commun. Mag.*, vol. 56, no. 5, pp. 102–107, May 2018.

[26] F. Al-Turjman, "Cognitive routing protocol for disaster-inspired Internet of Things," *Future Gener. Comput. Syst.*, vol. 92, pp. 1103–1115, Mar. 2019.

[27] D. Purkovic, M. Hönsch, and T. R. M. K. Meyer, "An energy efficient communication protocol for low power, energy harvesting sensor modules," *IEEE Sensors J.*, vol. 19, no. 2, pp. 701–714, Jan. 2019.

[28] K. Das, S. Das, R. K. Darji, and A. Mishra, "Energy efficient model for the sensor cloud systems," in *Proc. 2nd IEEE Int. Conf. Recent Trends Electron., Inf. Commun. Technol. (RTEICT)*, May 2017, pp. 373–375.

[29] K. Kaur, S. Garg, G. S. Aujla, N. Kumar, J. J. P. C. Rodrigues, and M. Guizani, "Edge computing in the industrial Internet of Things environment: Software-defined-networks-based edge-cloud interplay," *IEEE Commun. Mag.*, vol. 56, no. 2, pp. 44–51, Feb. 2018.

[30] F. Jalali, K. Hinton, R. Ayre, T. Alpcan, and R. S. Tucker, "Fog computing may help to save energy in cloud computing," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 5, pp. 1728–1739, May 2016.

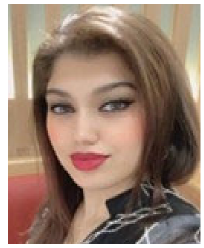
[31] M. Frey, F. Große, and M. Günes, "Energy-aware ant routing in wireless multi-hop networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2014, pp. 190–196.

[32] N. Javaid, T. Hafeez, Z. Wadud, N. Alrajeh, M. S. Alabed, and N. Guizani, "Establishing a cooperation-based and void node avoiding energy-efficient underwater WSN for a cloud," *IEEE Access*, vol. 5, pp. 11582–11593, May 2017.

[33] A. D. Kumbhar and M. K. Chavan, "An energy efficient ring routing protocol for wireless sensor network," in *Proc. Int. Conf. I-SMAC (IoT Social, Mobile, Analytics Cloud) (I-SMAC)*, Feb. 2017, pp. 909–913.

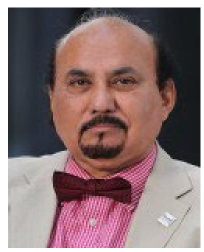
[34] A. Preethi, E. Pravin, and D. Sangeetha, "Modified balanced energy efficient network integrated super heterogeneous protocol," in *Proc. Int. Conf. Recent Trends Inf. Technol. (ICRTIT)*, Apr. 2016, pp. 1–6.

[35] W. Zhang, Y. Liu, G. Han, Y. Feng, and Y. Zhao, "An energy efficient and QoS aware routing algorithm based on data classification for industrial wireless sensor networks," *IEEE Access*, vol. 6, pp. 46495–46504, 2018.
[36] H. Mostafaei, "Energy-efficient algorithm for reliable routing of wireless sensor networks," *IEEE Trans. Ind. Electron.*, vol. 66, no. 7, pp. 5567–5575, Jul. 2019.
[37] J. Ren, Y. Zhang, N. Zhang, D. Zhang, and X. Shen, "Dynamic channel access to improve energy efficiency in cognitive radio sensor networks," *IEEE Trans. Wireless Commun.*, vol. 15, no. 5, pp. 3143–3156, May 2016.
[38] Y. Huang and Y. Hua, "Energy planning for progressive estimation in multihop sensor networks," *IEEE Trans. Signal Process.*, vol. 57, no. 10, pp. 4052–4065, Oct. 2009.
[39] D. Wu, G. Zhu, D. Zhao, and L. Liu, "Energy balancing in an OFDM-based WSN," in *Proc. IEEE 73rd Veh. Technol. Conf. (VTC Spring)*, May 2011, pp. 1–5.
[40] S. Li, Y. Tao, X. Qin, L. Liu, Z. Zhang, and P. Zhang, "Energy-aware mobile edge computation offloading for IoT over heterogenous networks," *IEEE Access*, vol. 7, pp. 13092–13105, 2019.
[41] W. Wang, Q. Zhang, H. Lin, M. Liu, X. Liang, and Q. Liu, "Wireless energy transmission channel modeling in resonant beam charging for IoT devices," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 3976–3986, Apr. 2019.
[42] I.-G. Lee and M. Kim, "Interference-aware self-optimizing Wi-Fi for high efficiency Internet of Things in dense networks," *Comput. Commun.*, vols. 89–90, pp. 60–74, Sep. 2016.
[43] M. J. Kang, S. Jeong, I. Yoon, and D. K. Noh, "Energy-aware determination of compression for low latency in solar-powered wireless sensor networks," *Int. J. Distrib. Sensor Netw.*, vol. 13, no. 2, Feb. 2017, Art. no. 155014771769416.
[44] B. C. Csáji, Z. Kemény, G. Pedone, A. Kuti, and J. Váncza, "Wireless multi-sensor networks for smart cities: A prototype system with statistical data analysis," *IEEE Sensors J.*, vol. 17, no. 23, pp. 7667–7676, Dec. 2017.
[45] F. Chiariotti, M. Condoluci, T. Mahmoodi, and A. Zanella, "SymbioCity: Smart cities for smarter networks," *Trans. Emerg. Telecommun. Technol.*, vol. 29, no. 1, p. e3206, Jan. 2018.
[46] W.-S. Jang, W. M. Healy, and M. J. Skibniewski, "Wireless sensor networks as part of a Web-based building environmental monitoring system," *Autom. Construct.*, vol. 17, no. 6, pp. 729–736, Aug. 2008.
[47] G. Shen and R. S. Tucker, "Energy-minimized design for IP over WDM networks," *J. Opt. Commun. Netw.*, vol. 1, no. 1, pp. 176–186, Jun. 2009.
[48] R. Niu, B. Chen, and P. K. Varshney, "Fusion of decisions transmitted over Rayleigh fading channels in wireless sensor networks," *IEEE Trans. Signal Process.*, vol. 54, no. 3, pp. 1018–1027, Mar. 2006.
[49] *Anonymous*. Accessed: Mar. 11, 2023. [Online]. Available: http://www.ti.com/lit/ds/symlink/cc3200.pdf
[50] *Anonymous*. Accessed: Mar. 11, 2023. [Online]. Available: https://www.seeedstudio.com/RedBearLab-CC3200-WiFiboard-p-2313.html
[51] *CC3200MOD SimpleLink Wi-Fi and Internet-of-Things Module Solution, a Single-Chip Wireless MCU SWRS166*, Texas Instrum., USA, Dec. 2014.



Halah Mohammed Al-Kadhim (Member, IEEE) received the B.Sc. and M.Sc. degrees in electronic and communication engineering from Baghdad University, Baghdad, Iraq, in 2008 and 2012, respectively, and the Ph.D. degree in electronic and electrical engineering from Brunel University London, Uxbridge, U.K., in 2020.

Her current research interests include the Internet of Things (IoT), cloud computing, energy efficiency, reliability, adaptive data compression, interference cancellation, fading channel gain, traffic power consumption, artificial intelligence (AI), and smart city applications.



Hamed S. Al-Raweshidy (Senior Member, IEEE) received the B.Eng. and M.Sc. degrees from the University of Technology, Baghdad, Iraq, in 1977 and 1980, respectively, the Post Graduate Diploma degree from Glasgow University, Glasgow, U.K., in 1987, and the Ph.D. degree from the University of Strathclyde, Glasgow, in 1991.

He was with the Space and Astronomy Research Centre, Baghdad, Iraq; PerkinElmer, Waltham, MA, USA; British Telecom, London, U.K.; Oxford University, Oxford, U.K.; Manchester Metropolitan University, Manchester, U.K.; and Kent University, Canterbury, U.K. He is currently the Director of the Wireless Network Communications Centre, Brunel University London, Uxbridge, U.K.