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Energy Efficient and Reliable Transport of Data in Cloud based IoT

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ABSTRACT The Internet of things (IoT) comprises a large number of sensor nodes with limited processing, storage, and battery abilities. The IoT has to operate in a constrained environment with specific challenges, such as hardware malfunctions, battery depletion, and harsh wireless environmental conditions. Deploying a reliable IoT is especially important for critical IoT applications such as smart cities. To ensure the quality of service requirements of these applications, the IoT needs to provide specific reliability guarantees. There are several strategies to ensure energy efficient and reliable transport of data in the IoT. However, there is an inherent conflict between power consumption and reliability: an increase in reliability usually leads to an increase in power consumption as in traditional retransmission-based reliability. To solve this problem, we present four scenarios of optimization using a mixed integer linear programming (MILP) model. First, we used a standby routes selection scheme (SBRS) to replace node failures and achieve reliability with minimum traffic power consumption. Second, we used a desired reliability level scheme (DRLS), which minimizes the traffic power consumption of IoT devices while considering the desired reliability level as a key factor. We also propose a reliability-based sub-channel scheme (RBS) to avoid overhead on busy reliable routes while mitigating interference. Moreover, we present a reliability-based data compression scheme (RBDS) to overcome capacity limits of the links. The results show that our proposed schemes reduce the negative effect between reliability and total traffic power consumption with average power saving of 57% in SBRS and 60% in RBDS compared to DRLS.

INDEX TERMS Cloud based IoT, data compression, energy efficiency, interference cancellation, Internet of things (IoT), reliability, traffic power consumption.

I. INTRODUCTION

The emergent Internet of Things (IoT) is thought to be the next generation of the Internet, in which billions of things are interconnected [1]. Example of these things are sensors, actuators, mobile phones and cars that are communicating with each other to perform service objective. Cloud computing is a new computing paradigm that enables users to elastically utilize a shared pool of cloud resources (e.g., processors, storage, applications, services) in an on-demand fashion. Recently, driven by the potential of complementing the ubiquitous data-gathering abilities of IoT devices with the powerful data storage and data processing capabilities of the cloud, the integration of the cloud and the IoT is attracting rising attention from both academia and industry [2]. Particularly, the data (alarm, security, climate, and entertainment) gathered by sensors are transmitted first to the gateway, which then transmits the received sensory data to the cloud. Eventually, the cloud stores, analyzes, processes, and transmits the sensed data to the users on demand. During the entire data transmission process, if the data transmission from the sensor nodes to the cloud is not succeeded, data are retransmitted until they are successfully delivered.

For this cloud based IoT prototype, the IoT acts as the data source for the cloud while users are the data requesters for the cloud. The users can have access to the needed sensory data from the cloud, whenever and wherever there is network connection. In these potential applications of cloud based IoT integration, such as smart buildings of smart cities [3, 4], a number of them require the IoT to reliably offer sensory data to the cloud, based on the requests of the users [5]. In general, sensors' limited battery power will be depleted by performing data sensing, processing, and transmission after a specific period of time, as they are usually supplied with non-rechargeable batteries and their replacement may also be unpractical [6]. A number of approaches have been evolved to optimize the power consumption (expanding the network lifetime) and improve the reliability (rising the probability of a packet being delivered) of IoT. However, approaches to reduce the power consumption contrarily impact the reliability of the network. An example of this approach is applied when part of the network works, whilst other parts sleep. This approach is excellent for power consumption, but not for reliability [7] because part of the network may be inaccessible due to an IoT node sleeping. Another example of this approach makes multiple paths between a specific IoT node and the gateway. In contrast to the previous example, this method is excellent for reliability, but not for power consumption because it will use more than one route, which means more IoT nodes to transmit the same packet. Therefore, it is important to assess the IoT reliability considering the traffic power consumption. In this work, we have considered that IoT network can fail in two points: links due to traffic congestion or interference and sensor nodes due to diminishing their energy. This paper proposes four models for achieving two goals, the energy efficiency of cloud based IoT considering the reliability level. For instance, to reduce total traffic power consumption, we used the following approaches: first, each model has the objective of minimization the total transmitted power by selecting the IoT device with lowest energy per bit and lowest idle power. Second, the usage of the data compression technique which reduces the amount of data to be transmitted. Thirdly, interference cancellation will reduce the retransmission of the data that has been lost due to interference. To achieve reliability objective, we proposed two approaches, first, is to select the reliable links that have a 99% reliability level. Second, is to select a standby link as an alternative to the link fail. Finally, each proposed scheme has two optimization objectives: energy efficiency and reliability.

The main contributions of this paper are summarized as follows:

- Virtualize cloud based IoT network using MILP model.
- Minimize the total traffic power of the cloud based IoT network through MILP optimization model.
- Minimize interference.
- Achieving reliability in the cloud based IoT network.
- Distributing traffic through the gateways to avoid traffic congestion to the cloud in IoT network.
- Handle more traffic demands by using data compression technique.
- Investigate jointly the issues regarding energy efficiency and reliability from the viewpoint of cloud based IoT integration.

This paper proposed four models related to the evaluation of cloud based IoT network: it considers the mote energy level as the main factor of failures of WSN nodes; it uses the routing algorithm to define the paths between different WSN regions and the sink node; and it automatically generates reliability models considering the aforementioned elements.

This paper further proposes four schemes consisting of a standby routes selection scheme (SBRS), a desired reliability level scheme (DRLS), a reliability-based sub-channel scheme (RBS), and a reliability-based data compression scheme (RBDS), aimed at improving the reliability of IoT networks and reducing total transmitted power. Specifically, a SBRS is used to selectively choose standby routes to overcome node failure problems and reduce transmission power. In addition, a DRLS is used when a specific reliability level is needed to guarantee the link reliability while minimizing transmission power. Furthermore, a RBS uses sub-channels to mitigate interference and reduce overhead on links that are utilized by several IoT devices due to its high reliability. Finally, an RBDS uses a sequential lossless entropy compression (S-LEC) data compression algorithm to overcome the capacity limits of the links and reduce transmission power.

In the rest of this paper, Section II introduces the related work, in Section III we describe the background to this research, and Section IV presents the cloud based IoT integration system model. Section V introduces the network optimization model of cloud based IoT. Section VI presents our model objectives by introducing SBRS, DRLS, RBS and RBDS and Section VII evaluates the model results. In Section VIII we state our conclusions of the research.

II. RELATED WORK

Many published papers consider the problem of reliability considering energy efficiency. In paper [8], they consider the problem of deploying a wireless sensor network (WSN) that meets a specified minimum level of reliability during its mission time at a minimum network deployment cost. An ant colony optimization algorithm coupled with a local search heuristic was proposed as a solution to minimize the internal interference, bandwidth usage and energy consumption throughout the network's mission time. In paper [9], the effect of the number of network coding packets on the energy consumption with the joint network-channel coding (JNCC) model was analysed and an adaptive dynamic energy consumption (ADEC) optimization scheme was proposed. In paper [10], a framework called the improved software defined WSN (improved SD-WSN) is introduced. They address the network management, coverage and node failure issues. A novel WSN-mobile cloud computing integration scheme is proposed in [11], which involves two parts: 1) a time and priority-based selective data transmission, and 2) a priority-based sleep scheduling algorithm for WSN to save energy consumption so it can collect and transmit data in a more reliable way. Paper [12], presents a transmission estimation codesign framework to achieve energy-efficient and reliable transmission for high-accuracy state estimation of industrial IoT systems. They present a similar fog-cloud hierarchical network architecture that reduces the computing burden of each sensor and the energy consumption of the overall system by integrating group-based communication and data aggregation technologies. In [13], to perform energy-efficient secure uplink transmission for the wireless powered IoT, the authors consider three relay selection schemes with the best power beacons (PBs) selected by the source, where one energy-constrained source and multiple energy-constrained relays harvest energy from multiple PBs in the presence of a passive eavesdropper. For each scheme, the exact closed-form expressions of power outage probability, secrecy outage probability, and secure energy efficiency are derived over the Rayleigh fading channel.

There is also much research into reliability in cloud based IoT: Paper [14], prototypes a smart energy IoT-cloud service. To facilitate reliable service operation, they adopted Docker Swarm-based container orchestration and verified its possibility of sustaining the service operation. Paper [11] combines IoT and the cloud to save energy consumption as mentioned earlier.

Research concerning reliability with existing interference include: In this work [15], they present a quality of service (QoS) framework for arbitrary hybrid wired/wireless networks, which guarantee that the delay bound and the target reliability of each application are provided. Additionally, they propose a reliability-based scheduler for WSN which is able to achieve target reliability in the presence of dynamic interference. In paper [8], they consider the problem of WSN reliability while minimizing internal interference throughout the network's mission time.

Paper [7], presents a WSN reliability model that is generated automatically from the WSN topology, information about adopted routing algorithms, and the mote battery level. They considered WSN failure links and sensor nodes. Paper [16] proposes three different methods implemented sequentially to detect and isolate three common sensor faults in a WSN-based wind turbine condition monitoring system: short fault, constant fault, and noise fault. Paper [17] proposes a wavelet- neural-network-based link quality estimation algorithm that closes the gap between the QoS requirements of smart grids and the features of radio links by estimating the probability-guaranteed limits on the packet reception ratio. In [18], the researchers model the failure behaviour of a mesh storage area network (SAN) system using a dynamic fault tree in the case of perfect links, or a network graph in the case of imperfect links. A binary decision diagram based method was then applied to assess the resultant fault tree model to generate reliability of the mesh SAN. In [19], they propose a reliable and lightweight trust mechanism for IoT edge devices based on multi-source feedback information fusion. They present a lightweight trust evaluating mechanism for cooperations of IoT edge devices, which is suitable for largescale IoT edge computing because it facilitates low-overhead trust computing algorithms. They adopted a feedback information fusion algorithm based on objective information entropy theory, which can overcome the limitations of traditional trust schemes. Paper [20], proposes a static time-slotted channel hopping (TSCH) scheduling scheme that permits all nodes in the TSCH network to transmit or receive frames in any slot. TSCH is a promising technology for the construction of reliable large-scale smart metering networks. To reduce network control message collisions, they defined the broadcast slots and unicast slots individually. In paper [21], a high flexible and reliable IoT platform was used that integrates fog computing and cloud computing (IFCIoT). Using IFCIoT, disaster monitoring systems and other application systems can be constructed. To deal with the impact of a failed component before performing certain special tasks, they propose a protocol that can achieve agreement among all fault free nodes with minimal rounds of message exchange and tolerate the maximum number of dormant and malicious faulty components in the IFCIoT platform.

Many research investigate the problem of energy efficiency of IoT. In paper [22], a low power, energy efficient communication protocol is proposed. The described protocol optimizes the way in which information is gathered from the environment, and packed and transmitted over long distances with minimum energy. It is particularly designed for energy constrained sensor modules which rely on energy harvesting. The collected information is transmitted in two different packet types named Teach-in and Data telegrams, respectively. Paper [23], proposes an efficient interactive model that is designed for sensor-cloud integration to enable the sensor-cloud to simultaneously provide sensing services on-demand to multiple applications with various latency requirements. The complicated functions were offloaded to the cloud, and only the light-weight processes were executed at resource constrained sensor nodes. They designed an aggregation mechanism for the sensor-cloud to aggregate the application requirements so that the workloads that are requested for sensors were minimized, thereby saving energy.

The MILP-based literature related to our study include: Paper [24], proposes a framework for an energy efficient cloud computing platform for Internet of things (IoT) along with a passive optical access network. The design is evaluated using MILP model, the energy efficiency is achieved by optimizing the placement and number of the mini clouds and Virtual Machines and utilizing energy efficient routes. This paper [1], had investigated the energy efficiency of service embedding framework in IoT networks of a smart city scenario by using the MILP. They developed a framework for optimizing the selection of IoT nodes and routes in the IoT network to meet the demands of the business process virtual nodes and links with the goal of minimizing the IoT system total power consumption. In [25], they investigate the use of fog computing for health monitoring applications. They developed a MILP model to optimise the placement of processing servers to process and analyse the Electrocardiogram signal from patients at the network edge. The locations of the processing servers are optimized so that the energy consumption of both the processing and networking equipment are minimized. In this paper [26], a real-time optimal energy management scheme is presented in a smart home by considering various demand response strategies such as the adoption of dynamic electricity price, and the installation of photovoltaic module and energy storage system. Both load scheduling problem of home appliances and energy dispatch problem of utility grid are formulated using MILP and solved under a single optimization framework, aiming to minimize the electricity cost required to satisfy the scheduled load demands. This research [27], implemented an automated real-time Heating Ventilation and Air Conditioning (HVAC) control system on top of an IoT framework, based on a thermal comfort optimization problem, demand response and majority user feedback. They use artificial neural networks to predict the thermal parameters of room based on historic time-series data. Where they optimize the HVAC control problem using MILP for an optimal energy efficiency-user comfort trade off. In this paper [28], They present a decentralized platform for implementing energy exchange mechanisms in a microgrid setting. Their proposed solution permits prosumers to trade energy without threatening their privacy or the safety of the system. Their hybrid MILP solver approach entitles the platform to clear offers securely and efficiently. an energy-centered and QoS-aware services selection approach (EQSA) for IoT environments is presented in [29]. Formulated and solved as a multi-objective optimization problem, this approach allows minimizing energy consumption to ensure a high availability of composite services while satisfying the user's QoS requirements. The proposed selection approach composed of preselecting the services offering the QoS level needed for user's satisfaction using a lexicographic optimization strategy and QoS constraints relaxation technique. By introducing the concept of relative dominance relation in the sense of Pareto, the preselected candidate services are then compared to select the best service. The relative dominance of a candidate service depends on its energy profile and QoS attributes, and user's preferences. The EQSA algorithm is scalable in time performance for large-scale IoT environments composed of thousands of distributed entities and is able to find very close-to-optimal solutions (about 98%).

However, these models did not assess the total traffic power consumption and reliability for the entire cloud based IoT network. Additionally, they do not consider network capacity and link overload as factors that affect the sensor node reliability and energy efficiency. In summary, none of the existing solutions provide a reliability model for cloud based IoT networks, or are able to provide a target reliability in the presence of dynamic interference without causing a higher level of power consumption.

III. BACKGROUND

A. Reliability of IoT network

In cloud based IoT integration, one aspect of IoT reliability relates to whether the IoT is constantly able to collect and transmit the sensed data to the cloud successfully. We discuss some critical issues regarding the reliability of IoT.

1) IoT device energy depletion

Energy depletion in IoT device is caused by the circuit power consumption and the power consumption of the transmitted signal, where the radio module is the main component that causes battery depletion of sensor nodes [30]. Principally, the sensors adjacent to the gateway serve as intermediate nodes that forward the packets to the gateway on behalf of the source nodes. Therefore, they may diminish their energy faster than other sensors and produce gaps in the IoT where data can’t be gathered for the cloud or result in IoT network disconnection.

2) Sensed data transmission failure

The data transmissions from one IoT device to another and to the cloud may face failures or losses, owing to several factors; for example, traffic congestion or interference [31], [32]. In such cases, if the IoT devices do not perform data retransmission, then the cloud cannot obtain the sensory data coming from the IoT network.

3) Storage space limitation for sensed data

Data storage is a serious issue for IoT, considering a large volume of gathered data needs to be archived for future information retrieval [33]. When there is not enough storage space to store the sensed data, then the cloud cannot attain any sensory data, even if the IoT devices have enough residual energy to collect and transmit data and the transmission to the cloud is successful. In this paper, we assume that sensors have sufficient storage space.

B. Overview of S-LEC data compression

Power consumption is a critical problem affecting the lifetime of IoT networks. A number of techniques have been proposed to solve this issue, one of the proposed techniques is the data compression scheme. It is used to reduce transmitted data over wireless channels. The format of the compressed data requires few bits, which leads to a minimization in the required inter-node communication, which is the main power consumer in the IoT. This will considerably lessen the energy demand, thus extending the lifetime of an IoT device.

One of the existing data compression approaches in IoT is sequential lossless entropy compression (S-LEC) [34]. S-LEC is capable of achieving highly robust compression performance for different sensor data streams simultaneously, and it enables energy-efficient employment and execution on resource-constrained WSN nodes in a relatively simple manner.

IV. Cloud based IoT integration system model

A cloud based IoT integration system is modelled in this paper based on the following assumptions:

We have a real-world scenario of smart buildings in a smart city with multiple user applications [35], [4], with the user application performing in the cloud and requesting data collection. The data are gathered by sensors in IoT devices, with the IoT devices having particular characteristics (functionality and location) and being connected to the cloud via the gateways. Physically, in the sensing and control layer, there are enormous numbers of IoT devices. Each IoT device is sending its collected data to the cloud continuously. The cloud has the computation abilities to analyze these data to satisfy the data requests from each corresponding user.

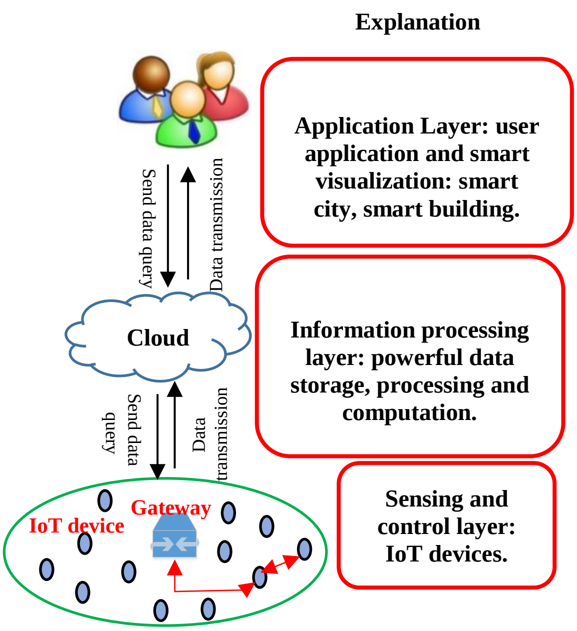

FIGURE 1. Architecture of cloud based IoT network

Cloud computing offers a platform as a service, through which the users can run, manage, and develop their applications. An example of data request is an application demand for real-time information; for instance, temperature or humidity, in a specified area in the city. The application layer will pass this request to the cloud. Then the cloud needs to process this and send the results to the application layer. To do so, the cloud will require these data from the IoT devices located in the involved area and then gather information via the gateways connected to it. The proposed architecture in our model is demonstrated in Fig.1 and it consists of three layers [36]:

1- Sensing and control layer: This comprises the low-powered sensors, actuators, and gateways. It collects the data and sends them for further analysis.

2- Information processing layer: The sensed data are in unprocessed form and in enormous volumes. To extract interpretable information from these data, they have to be stored, processed, and analyzed. These tasks are accomplished in this layer, which uses the cloud computing platform to afford storage and analytical data tools. It encompasses a data analytics centre, storage media, and different physical machines.

3- Application layer: This is in charge of the visualisation of the processed data and presents them in an inventive and simply readable form to the users. It introduces services to the end users by providing an interface for applications such as smart buildings.

The data is transmitted to the cloud through a gateway, which is due to the physical world (IoT network) being connected to the cloud and they having different protocols for communication.

V. Network optimization model of cloud based IoT

Our mathematical model is developed by means of mixed integer linear programming (MILP), which is mathematical programming that can perform optimization of a function of many variables subject to constraints. As clarified above, we have supposed a cloud based IoT system. The IoT devices are spread in one physical grid, in smart buildings, which comprises 45 IoT devices connected by a physical network distributed across three buildings, as shown in Fig. 2.

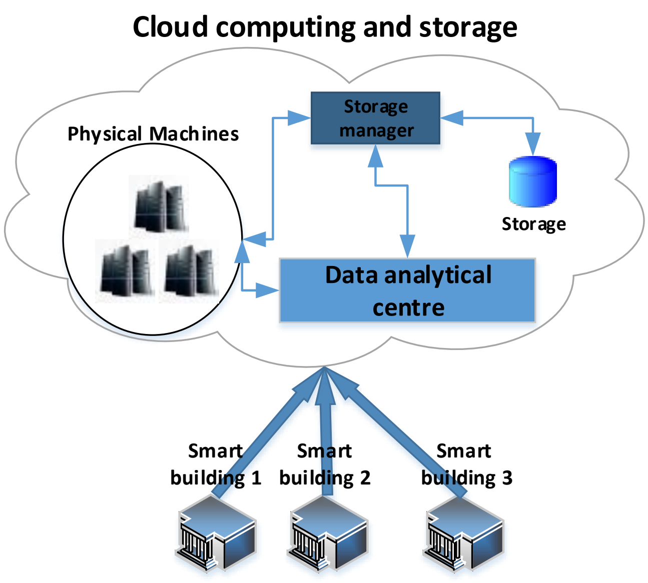

FIGURE 2. Physical network of a smart city

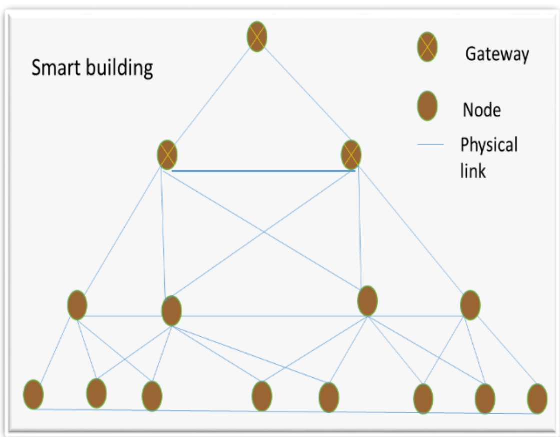

FIGURE 3. Topology of one of the smart buildings in the proposed IoT network of a smart city

We have supposed that these smart buildings (B) each have four floors (F), each with number of IoT devices. The nodes in the first and second floor of each building serves as a gateway to collect data to send to the cloud, as explained in Fig. 3. Each IoT device is linked to their neighbors through a physical plan. Each IoT device has the capability to process, store, and function. It is assumed that each IoT device includes two of the following functions: alarm, security, climate, and/or entertainment. The star topology of the IoT network is shown in Fig. 3, in which neighbored sensor nodes can communicate with each other and relay messages between them through the network [37].

VI. Objectives of the proposed model

The objective is to integrate reliability with minimum total traffic power consumption in the cloud based IoT network with less negative effect to each other. This is done through SBRS, DRLS, RBS and RBDS. We accomplish this by creating a parameter LK_G^d which indicates the traffic between the IoT device (d) and the cloud (G). The routing concept in this paper is based on the flow conservation constraint for the traffic flows in the physical network by Tuker [38]. It is also explained in our previous work [39]. We formed a binary variable $R_{i\ j}^{d\ \ G}$, which represents the route between the IoT device (d) and the cloud through the repeaters nodes *(i, j)* where *j* is neighbor of *i*.

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

$$\{\sum_{j\in NB[i]} R_{i\ j}^{d\ G} - \sum_{j\in NB[i]} R_{j\ i}^{d\ G}\} = \mathrm{LK}_G^d \quad (1)$$

$$\{\sum_{j\in NB[i]} R_{i\ j}^{d\ G} - \sum_{j\in NB[i]} R_{j\ i}^{d\ G}\} = 0 \quad (2)$$

$$\{\sum_{j\in NB[i]} R_{i\ j}^{d\ G} - \sum_{j\in NB[i]} R_{j\ i}^{d\ G}\} = -\,\mathrm{LK}_G^d \quad (3)$$

It states that if the traffic flowing into a node is the same traffic flowing out of a node, then the node is not a source or a destination. If the traffic out of the node minus the traffic entering the node equals the demand originating in the node, then it is a source. If the traffic that enters it minus the traffic that leaves it equals the demand destined to it (or the negative of the demand originating in the node as in (3)), then it is a destination. We briefly highlight lists of sets, parameters and variables defined in the MILP model in Tables I – III.

A. *Standby Routes Selection Scheme (SBRS):* The scope of this scheme is to optimally determine standby routers to be activated, in order to replace the node failures. The below constraint indicates that there are two routes, and one of them is standby:

$\forall\ d\ ,i\ ,\ \in \mathrm{D},\ j \in NB[i]\ ,i \neq j,\ d \neq G$

$$R1_{\ i\ j}^{\ d\ \ G} + R2_{\ i\ j}^{\ d\ \ G} \leq 1 \quad (4)$$

where, $R1_{\ i\ j}^{\ d\ \ G}$, $R2_{\ i\ j}^{\ d\ \ G}$: binary variables indicate route between IoT device and cloud through the repeater nodes *(i, j)*, where *j* is the neighbour of *i*.

The total traffic power consumption for this scenario is evaluated from the following constraint:

Objective: minimize

$$\sum_{i\in D} E_i * NT_i + \sum_i T1_{i\in D} * DL_i + \sum_i T2_{i\in D} * DL_i = TPS \quad (5)$$

where,

$T1_i$: Binary variable indicates the ON IoT devices for the first route.

$T2_i$: Binary variable indicates the ON IoT devices for the second route.

B. *Optimize the selection of reliable links (DRLS):* To ensure the route reliability, we proposed the following restriction that specifies the desired reliability level of each link for the whole path, which is 99% for this case:

TABLE I
List of the sets used in the MILP model

Set	Description
D	Set of devices.
sch	Set of sub-channels.
A	Set of data compression algorithms.
$NB[i]$	Set of the neighbors of the IoT device *i*.

TABLE II
List of the parameters used in the MILP model

Parameter	Description
LK_G^d	Traffic demands in kbps between sensor and cloud.
DL_i	The idle power of each node in mW.
RL_j^i	The reliability of each link in the IoT network
E_i	Energy per bit for each node in mW/kbps.
$TB_{\ G}^{\ i}$	The data traffic between the node and cloud before compression.
CP_a	The power consumed for compressing the data using the compression algorithm *a*.
CR_a	Compression ratio of the specific data compression algorithm a.

TABLE III
List of the variables used in the MILP model

Variable	Description
$R_{i\ j}^{d\ \ G}$	Full path route in physical plan between node and cloud through the repeaters nodes *(i, j)* where j is neighbor of *i*, IoT devices.
T_i	Indicator for the ON IoT devices.
$RC_{\ i\ j\ c}^{\ d\ \ G}$	The route between the IoT device *d* and the cloud *G* through the repeater nodes *(i, j)*, where *j* is the neighbour of *i*, through *c* sub-channel.
T_c^i	Indicator for the ON IoT device and the corresponding selected sub-channel *c*.
CI_a^i	Indicator for the IoT device and its corresponding compression algorithm.
TPS	The total traffic power consumption of the network for SBRS model in mW.
TP	The total traffic power consumption of the network for *DRLS* model in mW.
ST_G^i	The data traffic between the sensor node *(i)* and the cloud *(G)* after compression.
TPC	The total traffic power consumption in the network for RBDS model in mW.
NT_i	Variable indicate node traffic in kbps.

$\forall d, i \in D, j \in NB[i], i \neq j, d \neq G$

$$R_{ij}^{dG} * RL_j^i \geq R_{ij}^{dG} * 99\% \quad (6)$$

The following restriction evaluates the total traffic power in the network for this scenario.

Objective: minimize

$$\sum_{i \in D} E_i * NT_i + \sum_i T_{i \in D} * DL_i = TP \quad (7)$$

C. *Reliability-based sub-channel scheme (RBS):* In order to avoid overhead on busy reliable routes, we supposed that there are multiple channels for transmission, as illustrated in Table IV, which also reduce interference. To cancel the interference, we have adopted two constraints: First, there is only one traffic path between the device and the cloud.

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

$$\sum_{j \in NB[i], i \neq j} \sum_{c \in sch} RC_{ijc}^{dG} \leq 1 \quad (8)$$

Second, each IoT device must use only one sub-channel in each transmission or else zero, to avoid transmission repetition.

$\forall i \in D$

$$\sum_{c \in sch} T_c^i \leq 1 \quad (9)$$

Note that, these constraints are applicable for all other schemes to assure cancelling the interference.

D. *Reliability-based data compression scheme (RBDS):* To overcome the capacity limit of the links' Wi-Fi standard (10 Mbps for IEEE.802.11b), we used S-LEC data compression to reduce the size of transmitted data, which led to further reducing the transmission power. S-LEC has a 72.07% compression ratio with 2.897 mW/byte of compression power [34] and the desired link reliability is supposed to be 99%. The following constraint states the data traffic between the sensor node *(i)* and the cloud *(G)* after compression:

$\forall \; i \in D$

$$\sum_{a \in A} TB_G^i * CR_a * CI_a^i = ST_G^i \quad (10)$$

The following restriction evaluates the total traffic power consumption in the network for the RBDS scheme:

Objective: minimize

$$\sum_{i \in D} \sum_{a \in A} CI_a^i * CP_a + \sum_{i \in D} E_i * ST_G^i + \sum_i T_{i \in D} * DL_i = TPC \quad (11)$$

VII. EVALUATION RESULTS

To evaluate the performance of the above approaches, we compared the total traffic power consumption of the cloud based IoT network for our proposed schemes. The radio communication of the sensor nodes is Wi-Fi, based on 2.4 GHz frequency, and has an IEEE 802.11 standard. The values of the energy per bit (Ei) and the idle power ($IDLEi$) are real ones taken from different energy efficient IoT devices data sheets, namely: SPWF04SA, SPWF04SC datasheet [40], ESP32 datasheet [41], ESP8266EX datasheet [42], ZG2100M/ZG2101M Wi-Fi® Module data Sheet [43], CC3100 SimpleLink™ Wi-Fi® Network Processor, Internet-of-Things Solution for MCU Applications [44], CC3200MOD SimpleLink™ Wi-Fi® and the Internet-of-Things Module Solution, a Single-Chip Wireless MCU [45]. We assume that there is a smart city containing three smart buildings and each have 15 nodes distributed over four floors. Each building has three gateways. Each gateway gathers and transmits data to the cloud, enabling it to reply to data requests from each corresponding application user. The detailed evaluation parameters are summarized in Table IV.

TABLE IV
Evaluation Parameters

Parameter	Parameter value
Number of buildings	3
Number of sensor nodes per building	15
Number of gateways per building	3
Number of floors per building	4
Number of sub-channels	2
RL_j^i	90, 99
Capacity limit	10 Mbps
Radio communication standard	802.11

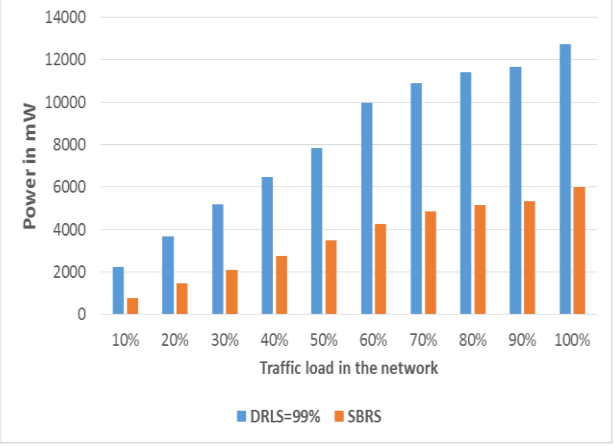

FIGURE 4. Total traffic power consumption in mW of a different number of devices when the link bit rate is 500 kbps for each node: a) energy efficient network optimization with DRLS =99% and b) energy efficient network optimization with SBRS.

The results in Fig. 4 display the total traffic power consumption of the cloud based IoT network in mW for DRLS and SBRS systems, versus different percentages of the number of IoT devices that generate 500 kbps of bit rate for each device. From Fig. 4, we can observe that there is an average power saving of 57% in the SBRS model compared to DRLS, which is due to selecting the minimum number of hops in SBRS, while DRLS has to select the 99% reliable routes for transmission, which could include a higher number of hops. Note that both models select efficient energy per bit and idle power IoT devices to minimize power.

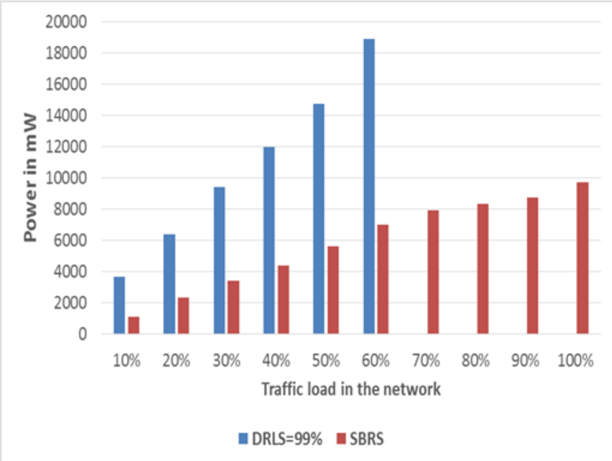

FIGURE 5. Total traffic power consumption in mW of a different number of devices when the link bit rate is 1000 kbps for each node: a) energy efficient network optimization with DRLS =99% and b) energy efficient network optimization with SBRS.

The results in Fig. 5 show the total traffic power consumption of the cloud based IoT network in mW for DRLS and SBRS systems, versus the different number of IoT devices that generate 1000 kbps of bit rate for each device. The results show that the network is fully working in DRLS as long as the traffic load is below 60%. However, when it rises above this, the network goes down due to packet drop out as a result of capacity limit. However, in SBRS, the network still works even when fully loaded because there are no overhead over links.

The total traffic power consumption of the cloud bas IoT network in mW for DRLS and RBDS systems, versus different number of IoT devices that generate 500 kbps of bit rate for each device is shown in Fig. 6. Where, for both models the desired link reliability supposed to be 99%. The results display that there is an average power saving of 60% in the RBDS model compared to DRLS, which is due to RBDS reduces the traffic of each node by compressing the data, in addition to selecting efficient energy per bit and idle power IoT devices for both schemes.

Fig. 7 displays the total traffic power consumption of the IoT network in mW for DRLS and RBDS systems, versus the same number of IoT devices which generate 1000 kbps of bit rate for each device. From Fig. 7, we can observe that for the RBDS model, the network still works when fully loaded with a link bit rate of 1000 kbps, even when the link reliability is 99%, due to minimizing the traffic using an S-LEC data compression scheme.

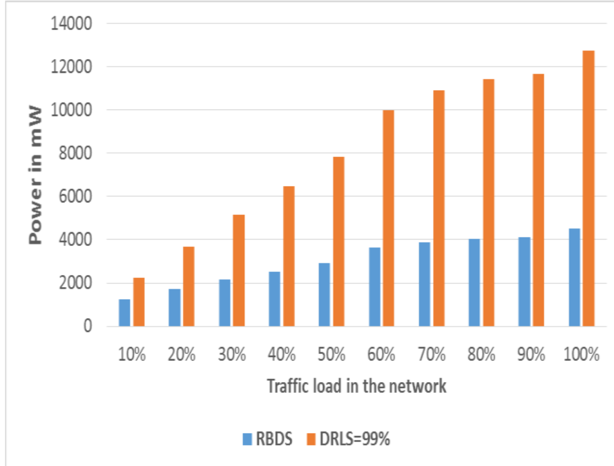

FIGURE 6. Total traffic power consumption of cloud based IoT network when the link bit rate is 500 kbps for each node: a) energy efficient network optimization with DRLS =99%; b) energy efficient network optimization with RBDS.

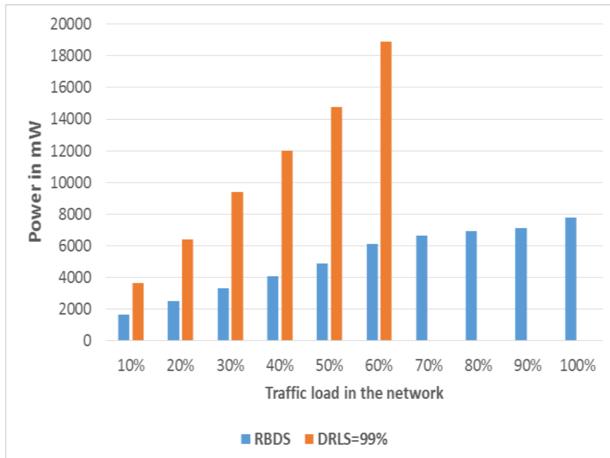

FIGURE 7. Total traffic power consumption of cloud based IoT network when the link bit rate is 1000 kbps for each node: a) energy efficient network optimization with DRLS =99%; b) energy efficient network optimization with RBDS.

The evaluation results with respect to multi-channel usage to avoid link overhead and reduce interference are shown in Fig. 8. It shows an example of the interference avoidance and displays IoT device distribution in one time slot for two sub-channels. It is clear that there is isolation between the nodes since they are served in different sub-channels.

The results in Fig. 9 show the total traffic power consumption of the cloud based IoT network in mW for two scenarios of DRLS, first with single channel and second with two channels when reliability level constrained to 99%, versus the different number of IoT devices that generate 1000 kbps of bit rate for each device. The results show that the network is fully working in DRLS with a single channel provided that the traffic load is below 60%. Nevertheless, when it increases above this, the network goes down owing to packet drop out due to capacity limitation. However, when the number of channels increased to two, the network still works whilst fully loaded since there is no overhead over links as a result of distributing the traffic load over the two channels available for each IoT device.

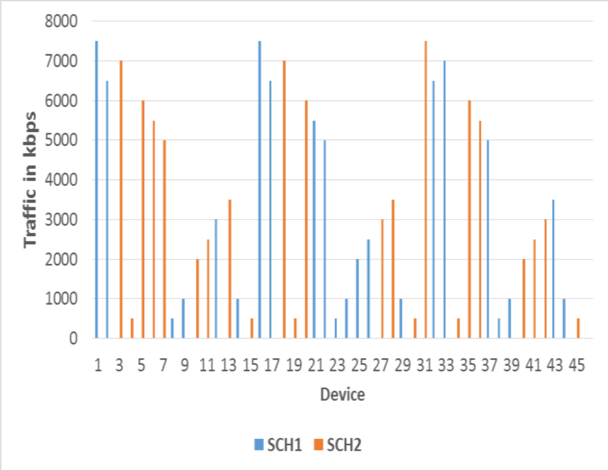

FIGURE 8. Interference avoidance by distribution of nodes on sub-channels

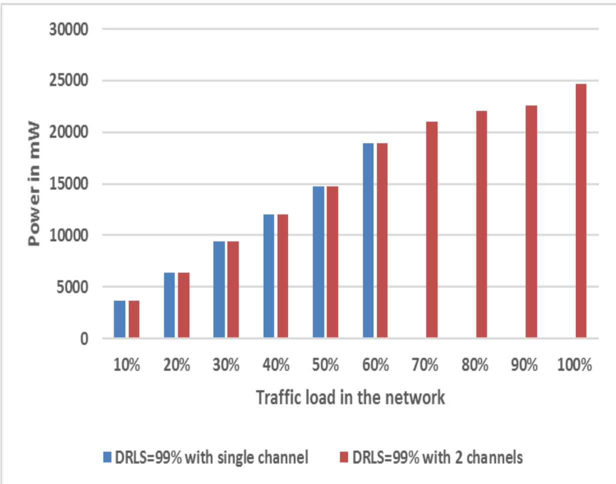

FIGURE 9. Total traffic power consumption in mW of a different number of IoT devices when the link bit rate is 1000 kbps for each node: a) energy efficient network optimization for DRLS =99% with a single channel and b) energy efficient network optimization for DRLS =99% with two channels.

VIII. CONCLUSION

In this paper, we have presented an MILP optimization model to address dual goals by achieving reliability and reducing total traffic power consumption in the cloud based IoT network. We proposed four optimization schemes: 1- DRLS that restricts the link reliability to certain percentage. 2- SBRS, which optimizes the selection of standby routes for node failures.3- RBDS that uses an S-LEC data compression scheme to overcome capacity limits and further reduce traffic power consumption, and 4- RBS that uses multiple channels to mitigate interference and avoid link overhead. The results indicate that the proposed schemes can significantly reduce energy consumption with an average power saving of 57% for SBRS and 60% for RBDS, compared to DRLS.

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REFERENCES

[1] H.Q. Al-Shammari, A. Lawey, T. El-Gorashi and J.M. Elmirghani, “Energy efficient service embedding in IoT networks,” *Wireless and Optical Communication Conference (WOCC), 27th.IEEE*, 2018, pp. 1-5.

[2] C. Zhu, Z. Sheng, V.C.M. Leung, L. Shu and L.T. Yang, “Toward Offering More Useful Data Reliably to Mobile Cloud From Wireless Sensor Network,” *IEEE Transactions on Emerging Topics in Computing*, vol. 3, no. 1, pp. 84-94, Mar. 2015.

[3] 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 Journal*, vol. 17, no. 23, pp. 7667-7676, Dec. 2017.

[4] F. Chiariotti, M. Condoluci, T. Mahmoodi and A. Zanella, “SymbioCity: Smart cities for smarter networks,” *Transactions on Emerging Telecommunications Technologies*, vol. 29, no. 1, pp. e3206-n/a, Jan. 2018.

[5] S. Chatterjee and S. Misra, “Target Tracking Using Sensor-Cloud: Sensor-Target Mapping in Presence of Overlapping Coverage,” *IEEE Communications Letters*, vol. 18, no. 8, pp. 1435-1438, Aug. 2014.

[6] M. Song and M. Zheng, “Energy Efficiency Optimization For Wireless Powered Sensor Networks With Nonorthogonal Multiple Access,” *IEEE sensors letters*, vol. 2, no. 1, pp. 1-4, Mar. 2018.

[7] A. Dâmaso, N. Rosa and P. Maciel, “Reliability of wireless sensor networks,” *Sensors*, vol. 14, no. 9, pp. 15760-15785, Aug. 2014.

[8] D.S. Deif and Y. Gadallah, “An Ant Colony Optimization Approach for the Deployment of Reliable Wireless Sensor Networks,” *IEEE Access*, vol. 5, pp. 10744-10756, 2017.

[9] X. Liu, N. Xiong, W. Li and Y. Xie, “An Optimization Scheme of Adaptive Dynamic Energy Consumption Based on Joint Network-Channel Coding in Wireless Sensor Networks,” *IEEE Sensors Journal*, vol. 15, no. 9, pp. 5158-5168, Sep. 2015.

[10] Y. Duan, W. Li, X. Fu, Y. Luo and L. Yang, “A methodology for reliability of WSN based on software defined network in adaptive industrial environment,” *IEEE/CAA Journal of Automatica Sinica*, vol. 5, no. 1, pp. 74-82, Jan. 2018.

[11] C. Zhu, Z. Sheng, V.C.M. Leung, L. Shu and L.T. Yang, “Toward Offering More Useful Data Reliably to Mobile Cloud From Wireless Sensor Network,” *IEEE Transactions on Emerging Topics in Computing*, vol. 3, no. 1, pp. 84-94, Mar. 2015.

[12] L. Lyu, C. Chen, S. Zhu and X. Guan, “5G Enabled Codesign of Energy-Efficient Transmission and Estimation for Industrial IoT Systems,” *IEEE Transactions on Industrial Informatics*, vol. 14, no. 6, pp. 2690-2704, June 2018.

[13] Y. Wang, W. Yang, X. Shang, J. Hu, Y. Huang and Y. Cai, “Energy-Efficient Secure Transmission for Wireless Powered Internet of Things With Multiple Power Beacons,” *IEEE Access*, vol. 6, pp. 75086-75098, Dec. 2018.

[14] S. Kim, C. Kim and J. Kim, “Reliable smart energy IoT-cloud service operation with container orchestration,” *2017 19th Asia-Pacific Network Operations and Management Symposium (APNOMS). IEEE*, pp. 378-381, Sep. 2017.

[15] S. Zoppi, A. Van Bemten, H.M. Gursu, M. Vilgelm, J. Guck and W. Kellerer, “Achieving Hybrid Wired/Wireless Industrial Networks With WDetServ: Reliability-Based Scheduling for Delay Guarantees,” *IEEE Transactions on Industrial Informatics*, vol. 14, no. 5, pp. 2307-2319, May 2018.

[16] Y. Peng, W. Qiao, L. Qu and J. Wang, “Sensor Fault Detection and Isolation for a Wireless Sensor Network-Based Remote Wind Turbine Condition Monitoring System,” *IEEE Transactions on Industry Applications*, vol. 54, no. 2, pp. 1072-1079, Mar. 2018.

[17] W. Sun, W. Lu, Q. Li, L. Chen, D. Mu and X. Yuan, “WNN-LQE: Wavelet-Neural-Network-Based Link Quality Estimation for Smart Grid WSNs,” *IEEE Access*, vol. 5, pp. 12788-12797, 2017.

[18] L. Xing, M. Tannous, V.M. Vokkarane, H. Wang and J. Guo, "Reliability Modeling of Mesh Storage Area Networks for Internet of Things," *IEEE Internet of Things Journal*, vol. 4, no. 6, pp. 2047-2057, Dec. 2017.
[19] J. Yuan and X. Li, "A Reliable and Lightweight Trust Computing Mechanism for IoT Edge Devices Based on Multi-Source Feedback Information Fusion," *IEEE Access*, vol. 6, pp. 23626-23638, May 2018.
[20] H. Park, H. Kim, K.T. Kim, S. Kim and P. Mah, "Frame-Type-Aware Static Time Slotted Channel Hopping Scheduling Scheme for Large-Scale Smart Metering Networks," *IEEE Access*, vol. 7, pp. 2200-2209, 2019.
[21] S. Wang, S. Tseng, K. Yan and Y. Tsai, "Reaching Agreement in an Integrated Fog Cloud IoT," *IEEE Access*, vol. 6, pp. 64515-64524, Nov. 2018.
[22] D. Purkovic, M. Honsch and T.R.M.K. Meyer, "An Energy Efficient Communication Protocol for Low Power, Energy Harvesting Sensor Modules," *IEEE Sensors Journal*, vol. 19, no. 2, pp. 701-714, Jan. 2019.
[23] N. Dinh and Y. Kim, "An Efficient On-Demand Latency Guaranteed Interactive Model for Sensor-Cloud," *IEEE Access*, vol. 6, pp. 68596-68611, 2018.
[24] Z. T. Al-Azez, A. Q. Lawey, T. E. H. El-Gorashi and J. M. H. Elmirghani, "Energy efficient IoT virtualization framework with passive optical access networks," *2016 18th International Conference on Transparent Optical Networks (ICTON)*, 2016, pp. 1-4.
[25] I. S. M. Isa, M. O. I. Musa, T. E. H. El-Gorashi, A. Q. Lawey and J. M. H. Elmirghani, "Energy Efficiency of Fog Computing Health Monitoring Applications," *2018 20th International Conference on Transparent Optical Networks (ICTON)*, 2018, pp. 1-5.
[26] L. Yao, J. Shen and W. H. Lim, "Real-Time Energy Management Optimization for Smart Household," *2016 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)*, 2016, pp. 20-26.
[27] A. Rajith, S. Soki and M. Hiroshi, "Real-time optimized HVAC control system on top of an IoT framework," *2018 Third International Conference on Fog and Mobile Edge Computing (FMEC)*, 2018, pp. 181-186.
[28] A. Laszka, S. Eisele, A. Dubey, G. Karsai and K. Kvaternik, "TRANSAX: A Blockchain-Based Decentralized Forward-Trading Energy Exchanged for Transactive Microgrids," *2018 IEEE 24th International Conference on Parallel and Distributed Systems (ICPADS)*, 2018, pp. 918-927.
[29] M.E. Khanouche, Y. Amirat, A. Chibani, M. Kerkar and A. Yachir, "Energy-Centered and QoS-Aware Services Selection for Internet of Things," *IEEE Transactions on Automation Science and Engineering*, vol. 13, no. 3, pp. 1256-1269, Jul. 2016.
[30] T. Rault, A. Bouabdallah and Y. Challal, "Energy efficiency in wireless sensor networks: A top-down survey," *Computer Networks*, vol. 67, no. 4, pp. 104-122, Jul. 2014.
[31] F. Hu, Y. Xiao and Q. Hao, "Congestion-aware, loss-resilient bio-monitoring sensor networking for mobile health applications," *IEEE Journal on Selected Areas in Communications*, vol. 27, no. 4, pp. 450-465, May 2009.
[32] W. Fang, J. Chen, L. Shu, T. Shu Chu, D. Qian, "Congestion avoidance, detection and alleviation in wireless sensor networks," *Journal of Zhejiang University SCIENCE C*, vol. 11, no. 1, pp. 63-73, Jan. 2010.
[33] B. Sheng, Q. Li and W. Mao, "Optimize Storage Placement in Sensor Networks," *IEEE Transactions on Mobile Computing*, vol. 9, no. 10, pp. 1437-1450, Oct. 2010.
[34] Y. Liang and Y. Li, "An Efficient and Robust Data Compression Algorithm in Wireless Sensor Networks," *IEEE Communications Letters*, vol. 18, no. 3, pp. 439-442, Mar. 2014.
[35] C. B. C., P. Z. Kemény G., K. A. and V. J., "Wireless multi-sensor networks for smart cities: a prototype system with statistical data analysi," *IEEE Sensors Journal*, vol. 17, no. 23, pp. 7667-7676, Dec. 2017.
[36] T. Baker, M. Asim, H. Tawfik, B. Aldawsari and R. Buyya, "An energy-aware service composition algorithm for multiple cloud-based IoT applications," *Journal of Network and Computer Applications*, vol. 89, pp. 96-108, July 2017.
[37] W. Jang, W.M. Healy and M.J. Skibniewski, "Wireless sensor networks as part of a web-based building environmental monitoring system," *Automation in Construction*, vol. 17, no. 6, pp. 729-736, Aug. 2008.
[38] G. Shen and R.S. Tucker, "Energy-Minimized Design for IP Over WDM Networks," *IEEE/OSA Journal of Optical Communications and Networking*, vol. 1, no. 1, pp. 176-186, June 2009.
[39] H. Al-Kadhim and H. Al-Raweshidy, "Energy Efficient Traffic in Cloud based IoT," *International Conference on Industrial Internet of Things and Smart Manufacturing Imperial College London, London, United Kingdom, 2018, ISBN: 978-1-912532-06-3 (Accepted and In process for Publication).*
[40] STMicroelectronics, "SPWF04SA, SPWF04SC Standalone and Serial-to-Wi-Fi b/g/n intelligent modules," *DocID029757 Rev 5*, Nov. 2017.
[41] S. Espressif, "ESP32 Datasheet,", June 2017.
[42] p. Espressif, "ESP8266EX Datasheet," *Version 5.8*, 2018.
[43] T. Microchip, "ZG2100M M /ZG2101M Wi-Fi® Module Data Sheet 2.4 GHz 802.11b Low Power Transceiver Module," *DS70624A*, 2010.
[44] I. Texas, "CC3100 SimpleLink™ Wi-Fi® Network Processor, Internet-of-Things Solution for MCU Applications," *SWAS031D*, June, 2013 [Revised Feb. 2015].
[45] I. Texas, "CC3200MOD SimpleLink™ Wi-Fi® and Internet-of-Things Module Solution, a Single-Chip Wireless MCU," *SWRS166*, Dec. 2014.