Energy Efficient Transmission in Cloud based IoT

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To my mother and father, to the great martyr my brother captain pilot "Ahmed Mohammed Al-Kadhim" the symbol of sacrifice, to my husband "Haider Q. Al-Shammari", to my son "Ali Al-Shammari", to my brother Hussein Al-Kadhim, to my sisters Marwah, Sarah, Ayaat and Fatemah; this thesis is dedicated to you.

Abstract

This thesis researched energy efficiency and reliability methodologies in the cloud based IoT. This thesis presents three contributions; the first one considers achieving reliability alongside minimum total traffic power consumption in the IoT network. The other two contributions provide solutions to minimise the IoT network power consumption by two aspects: radio power consumption and circuit power consumption minimisation.

Firstly, four scenarios of optimisation have been presented using mixed integer linear programming (MILP) model. 1- A standby routes selection scheme (SBRS) for replacing node failures to achieve reliability with minimum traffic power consumption. 2- The desired reliability level scheme (DRLS), where there is a minimisation of the traffic power consumption of IoT devices while considering the desired reliability level as a key factor. 3- The reliability-based sub-channel scheme (RBS) to avoid overhead on busy reliable routes while mitigating interference. 4- The reliability-based data compression scheme (RBDS) to overcome the capacity limits of the links. The results show that our proposed schemes have reduced the negative effect between reliability and total traffic power consumption with an average power saving of 57% in SBRS and 60% in RBDS compared to DRLS.

Secondly, an energy efficient cloud based IoT network design is introduced, through optimisation of the sensor selection, choosing the shortest routing path and exploiting fading sub-channel gain to reduce total traffic power and cancel interference. The optimisation model and results have been conducted using the MILP. The model evaluates the results for two scenarios: first, energy efficient network optimisation by minimum hops and then comparing the results with the second scenario of energy efficient network optimisation by minimum hops and sub-channel selection. From the results, it is concluded that the first scenario consumes more traffic power in IoT devices. In contrast, the second minimises the traffic power of the network by an average power saving of 27%.

Finally, an adaptive data compression scheme (ADCS) is proposed for efficiently controlling the compression rate and energy consumption in IoT devices. The model selects the optimal energy efficient data compression algorithm for each IoT device while taking

into consideration the IoT device processing capability, available energy in each IoT device battery and the amount of compression power. The result verifies that the proposed ADCS scheme saves power by an average of 40% compared to the non-compression scheme (NCS). This power saving is due to reducing the traffic load and the number of hops in the network, which lead to handle more traffic demands and increase the lifetime of IoT devices by 50%, compared to NCS system.

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Chapter 1

1 Introduction

1.1 Research Background

The rapid growth of the notion of the Internet of Things (IoT) and the fast development of technologies like short range mobile communication, is predicted to create a ubiquitous connection of ‘things’. Currently, there has been a growing interest in the capability of ‘smart’ objects to communicate and form a pervasive cyber-physical world. The emergent 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 objectives.

Moreover, this pervasive connection of ‘things’ will inevitably give rise to the generation of a massive amount of data, which need to be processed, stored, and accessed. IoT devices are restricted in terms of processor speed, storage and power. Cloud computing has longstanding been recognised as a prototype for massive data storage and analyses in an efficient way it allows users to utilise a shared pool of resources (e.g., processors, storage, applications, services) on demand. Recently, driven by the potential of complementing the ubiquitous data-gathering abilities of IoT devices with the sturdy 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]. The combining of cloud computing and IoT can permit ubiquitous sensing services and forceful processing of sensing data signals exceed the capability of single things, hence stimulating inventions in both fields.

For instance, cloud platforms permit the sensing data to be stored and utilised in an intelligent way for smart monitoring and actuation with smart devices. Different techniques can be executed and run centralised or distributed on the cloud to realize automated decision making, an example of these techniques are novel algorithms for data merging, methods for machine learning, and artificial intelligence. These techniques will boost the evolution of new applications, for example, transportation and smart cities systems, as shown in Figure 1-1 [3]. Notably, in Figure 1-1, the data (alarm, security, climate, and entertainment) gathered by sensors are transmitted first to the gateway, which then sends the received sensory data to the cloud. Eventually, the cloud stores, analyses, processes, and transmits the sensed data to the users of applications on demand. 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 through the internet. Smart buildings applications involve incorporating IoT into their infrastructure. Consequently, making modern buildings smart is a significant step towards smart cities that will enable future automation and optimisation. Smart buildings also improve energy management by minimising energy loss through intelligent control of the high energy requirements of building devices.

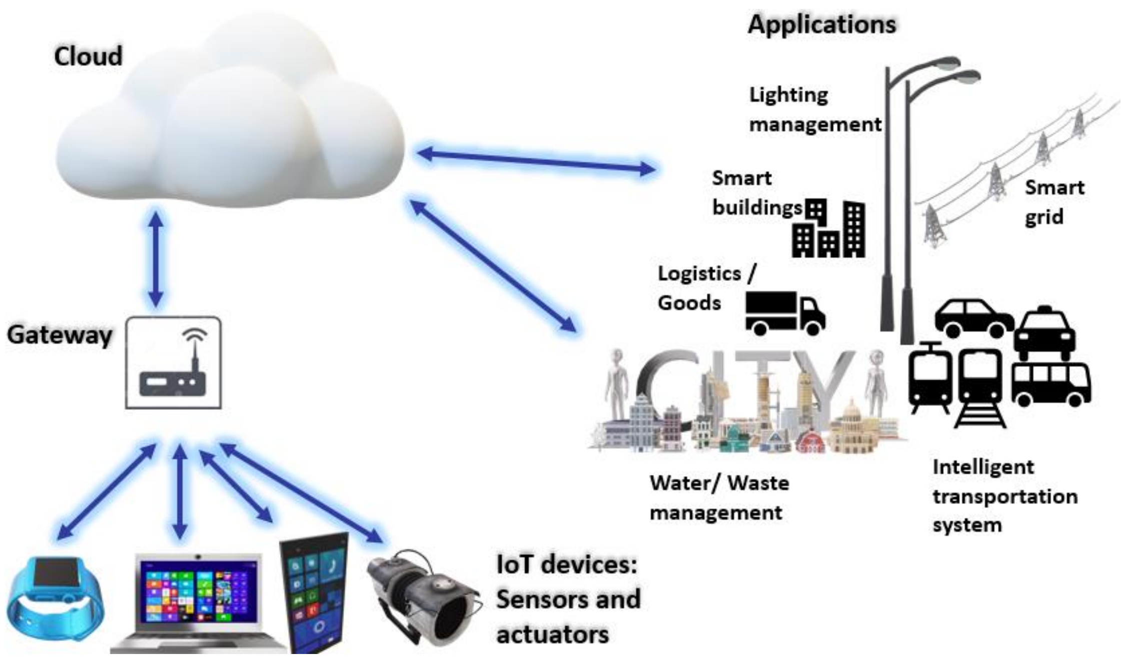


Figure 1-1: Graphical example of smart city applications in cloud based IoT.

The significance of the IoT draw the attention of many global institutions to research and explore in this field. IoT presents the interconnecting of the physical world with cyberspace, as a result of that, some fundamental concepts and critical issues have been predicted for the future internet. One of these issues is energy efficiency, which presents a crucial factor that should be taken into consideration in the designation of the future internet, which integrate the IoT. IoT comprises a large number of sensor nodes with limited processing, storage, and battery abilities. IoT has to operate in a constrained environment with specific challenges such as hardware malfunctions, battery depletion and harsh wireless environmental conditions.

Deploying reliable IoT is especially crucial for critical IoT applications, such as smart city [4]. In general, sensors' limited battery power will be depleted by performing data sensing, processing, and transmission after a specific time, as they are usually supplied with non-rechargeable batteries, and their replacement may also be unpractical [5]. To ensure the quality of service (QoS) requirements of these applications, IoT needs to provide specific reliability guarantees; there are several strategies to ensure energy efficient and reliable transport of data in 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. The prime goal of this thesis is to focus attention on the importance of energy efficiency and reliability of the cloud based IoT network while optimising the allocation of the tasks into the physical layer of IoT devices via the cloud platforms.

1.2 Motivation

It was stated that the information and communication technology (ICT) takes a global share of 4.7% of electricity usage in 2012 and 14% in 2020 [6], this statistic represents operational consumption only, thus without considering the manufacturing. This portion of power consumption in ICT sector mainly comes from data centres, user equipment and networking infrastructure. IoT has many applications that deployed most aspects of our life. For example, there is much research about smart home/office, smart water, smart transportation, smart agriculture/forest and smart cities [7].

Along with the development of wireless communication, IoT applications become wide perception in energy efficiency scope. For example, the personal and home IoT application harvests electricity usage data in the house and presented it to the electricity (utility) company to optimise the supply and demand according to this collected data from IoT devices. Besides, these applications have including more sensors and actuators which detect motion, temperature and humidity to harvest data that utilised to adjust the air conditioner accurately for a more convenient level of living for users with optimised use of energy. Therefore, IoT emanates different applications for improving energy efficiency such as home automation, healthcare and manufacturing. IoT network is called a smart network since it includes intelligent devices that work independently with its sensing, actuation, computation and communication capabilities [8].

Most of IoT devices have low power resource with short intervals due to most of them are battery powered, then care should be taken when operating those devices because of the difficulty and cost in replacing the battery. They may diminish their energy and produce gaps in the IoT network where data cannot be gathered for the cloud. Also, energy diminishing may result in the IoT network disconnection that affects the network reliability, whereas, some applications such as smart cities, require the data to be reliably delivered to the cloud and further to the user. So that energy is the main source factor in the IoT network. A solution for this issue is to use an efficient way to operate them and ensure their reliability besides that will deliver a more extended network lifetime.

1.3 Aims and Objectives

1.3.1 Aims

- Minimising the total transmission power consumption in cloud based IoT system:

  Reducing the power consumption of the IoT system that is integrated with cloud computing to enable continuous monitoring and sensing of physical things in the world. Energy efficiency is a critical aspect in IoT 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.

- Improving reliability in the cloud based IoT network:

  Enhancing the ability of the IoT devices to continually collect and transmit the sensed data to the cloud successfully.

1.3.2 Objectives

- Minimising traffic power consumption:

  Reducing transmission power of the network because the radio module is the main component that causes battery depletion of sensor nodes. Transmitted power has been minimised here through exploiting fading sub-channel gain and reducing the number of hops in the IoT network.

- Minimising computation power consumption:

  Data compression scheme reduces transmitted data over wireless channels since the format of the compressed data requires a few bits only, thus minimising the power needed in the computation process of the data.

- Maximising network lifetime:

  Providing energy efficiency in an IoT network does not guarantee that the battery life of a device will be longer. Hence, it is essential to consider the energy level of the battery for each IoT device before transmission and the data compression process by constraining battery level to be within 10% of total battery level to increase its lifetime.

- Minimising interference:

  Interference increases the probability of packets collision and reduces the performance of wireless communications. Interference will affect the reliability and contributes further to the power depletion in the nodes due to the data retransmission. Interference has been reduced here through the multiple channels approach for transmission.

- Avoid traffic congestion:

  Distributing traffic through multiple gateways to avoid traffic congestion to the cloud in the IoT network.

- Utilise network capacity:

  Utilising network capacity through handling more traffic demands due to using the data compression schemes.

- Ensure reliability by using 99% reliable links or by using standby routes:

  In this thesis, two approaches are proposed to achieve reliability objective; first, is to select the reliable links that have a 99% reliability level. Second, is to choose a standby link as an alternative to the link fail. Finally, each proposed scheme has two optimisation objectives: energy efficiency and reliability.

1.4 Contributions

This thesis has three contributions; a summary for each one is as follows:

- **Energy Efficient and Reliable Transport of Data in Cloud based IoT**

In **chapter three** of this work, a mixed integer linear programming (MILP) optimisation model is presented to address a dual goal by achieving reliability and reducing total traffic power consumption in the cloud based IoT network. Four optimisation schemes are proposed named: 1- Desired reliability level scheme (DRLS) that restrict the link reliability to 99%. 2- Standby routes selection scheme (SBRS) which optimise the selection of standby routes for node failures. 3- Reliability-based data compression scheme (RBDS) that uses a sequential lossless entropy compression (S-LEC) data compression scheme to overcome capacity limits and further reduce total traffic power consumption. Moreover, 4- Reliability-based sub-channel scheme (RBS) that uses multi-channel to mitigate interference and avoid link overhead. The performance of the proposed schemes have been analysed and compared in metric of energy efficiency.

- **Energy Efficient Traffic in Cloud based IoT**

Radio power consumption minimisation through:

- Optimising the network path with a minimum number of hops.

- Optimising sub-channel selection by exploiting fading channel gain.

This part of the work is accomplished in **chapter four** of this thesis, as explained briefly below:

A network optimisation model is introduced to reduce the total traffic power consumption in cloud based IoT network by exploiting the fading sub-channel gain and minimising the number of hops, besides of reduction of sub-channel interference. Two scenarios of optimisation are devised, the first pertaining to energy efficient network optimisation by minimising hops. In this scenario, the model minimises the number of hops and randomly selects the sub-channels. The second scenario involves energy efficient network optimisation by minimising hops and introducing energy efficient sub-channel selection. That is, the total traffic power is minimised through the selection of the highest fading sub-channel gain in addition to minimising the number of hops in the network. The two scenarios have been compared in terms of energy efficiency.

- **Energy Efficient Data Compression in Cloud based IoT**

Circuit power consumption minimisation through:

- Constrains battery level to be within 10% of total battery level to increase the lifetime and the tasks cycles for each IoT device.

- Optimise the selection of IoT devices with minimum energy per bit and idle power.

This part is presented in **chapter five** of the thesis as follows:

A network optimisation model of ADCS is introduced to reduce the total traffic power consumption in a cloud based IoT network. ADCS selects the energy efficient data compression algorithm, while also considering the IoT device battery level (10% of total battery level), its processing capability and compression power of the algorithm. The performance of the proposed ADCS (Sensor Lempel–Ziv–Welch (S-LZW) and S-LEC) system has been validated and compared to the non-compression scheme (NCS).

1.5 Publications

Published

1. H. M. Al-Kadhim and H. S. Al-Raweshidy, "Energy Efficient and Reliable Transport of Data in Cloud-Based IoT," in *IEEE Access*, vol. 7, pp. 64641-64650, 2019.
2. H. Al-Kadhim and H. Al-Raweshidy, "Energy Efficient Traffic in Cloud based IoT," International Conference on Industrial Internet of Things and Smart Manufacturing (IoTsm), Imperial College London, London, United Kingdom, 2018, ISBN: 978-1-912532-06-3.

Submitted

3. Halah Mohammed Al-Kadhim and Hamed S. Al-Raweshidy, "Energy Efficient Data Compression in Cloud based IoT", IEEE Sensors Journal.

1.6 Thesis Organization

The remainder of this thesis is organised as follows:

Chapter 2 - gives a brief introductory background of the research work presented in this thesis. It begins by providing an overview of the IoT system and its development, besides IoT enabling technologies, IoT elements, IoT communication technologies as well as the applications, architecture and routing technologies in IoT. Then an overview of cloud computing technology is produced. After that, a literature review is carried out on IoT energy efficiency and reliability challenges. Following that is an explanation of the research methodology towards the end of the chapter.

Chapter 3 - studies the energy efficiency and reliability in the cloud based IoT. It begins by providing a brief introduction about the reliability in the IoT network and how it is related to energy efficiency. Next, it presents the network optimisation model of cloud based IoT. Then, it introduces the system model objectives, followed by explaining the proposed SBRS and DRLS schemes used to provide reliability. Then, the proposed RBS scheme to cancel interference is presented. After that, the chapter provides the proposed RBDS scheme to reduce power consumption further. Finally, MILP simulation results, which evaluate and compare the performance and energy efficiency of the proposed scenarios, are shown.

Chapter 4 - studies energy efficient network optimisation through fading sub-channel gain selection in the cloud based IoT network. It begins by providing a brief introduction about the cloud based IoT system, and the proposed architecture. Then, the three main objectives of minimising the number of hops, interference cancellation and maximising fading channel gain, and their proposed MILP models are described in detail. Finally, MILP simulation results, which evaluate the total power consumption of the proposed scenarios and compare them, are provided.

Chapter 5 - investigates energy efficient network optimisation through ADCS in the cloud based IoT. It begins by providing essential background on data compression techniques. Next, it presents the adaptive data compression scheme and its main objectives. That is followed by outlining the proposed MILP models for achieving energy efficiency and maximising network lifetime. Finally, MILP simulation results, which evaluate and compare the performance and energy efficiency of the proposed scenarios, are plotted.

Chapter 6 - concludes the thesis, explains the work impact and suggests possible future works.

Chapter 2

2 Principles of IoT and Cloud Computing

2.1 Evolution of the Internet of Things (IoT)

Internet of Things (IoT) can be defined as an innovated paradigm that use advanced wireless communications to interconnect diversity of things. Example of these things are sensors, actuators, mobile phones and cars that are communicating with each other to perform service objective [4, 9, 10]. Historically, the concept of the Internet of Things was proposed by MIT Auto-ID labs in 1999 by Kevin Ashton [11]. Generally, IoT has plenty of meaning in terms of 'Internet' or 'Things', for instance, IoT refers to a worldwide network that interconnects all things encirclement by a human through utilising advanced communication technologies. Also, IoT could be indicated as a physical object 'things' that can react with each other and collaborate with their neighbours to achieve common goals [9]. In 2005, International Telecommunication Union (ITU) produced Internet of Things' report, officially suggested the trend of the Internet of Things, which illustrated that ubiquitous Internet of Things communication aeon began, wherein the exchange of information between all objects in the world through the networks can perform actively [12]. In fact, by 2020 there will be 50 billion IoT devices [13], this excessive number of interconnected devices, require accurate mapping and considering important factors such as energy efficiency, mobility, reliability, coverage, link capacity, and device cost. One of the definitions of IoT is that it is a ubiquitous system that planning and interconnecting 'things' between the physical 'real' world and cyber 'virtual' world. Things of IoT, refer to all ubiquitous and heterogynous things in the physical world, which refer to solid things with substantial forms and capable of dealing with specific situations in the physical world [14], whereas the cyber world point to services, cyber actions, and cyber entities (i.e. applications). In other words, cyber world indicts the logical functions that a thing can produce to implement specific task [15]. Figure 2-1 shows the IoT network with some examples of its applications.

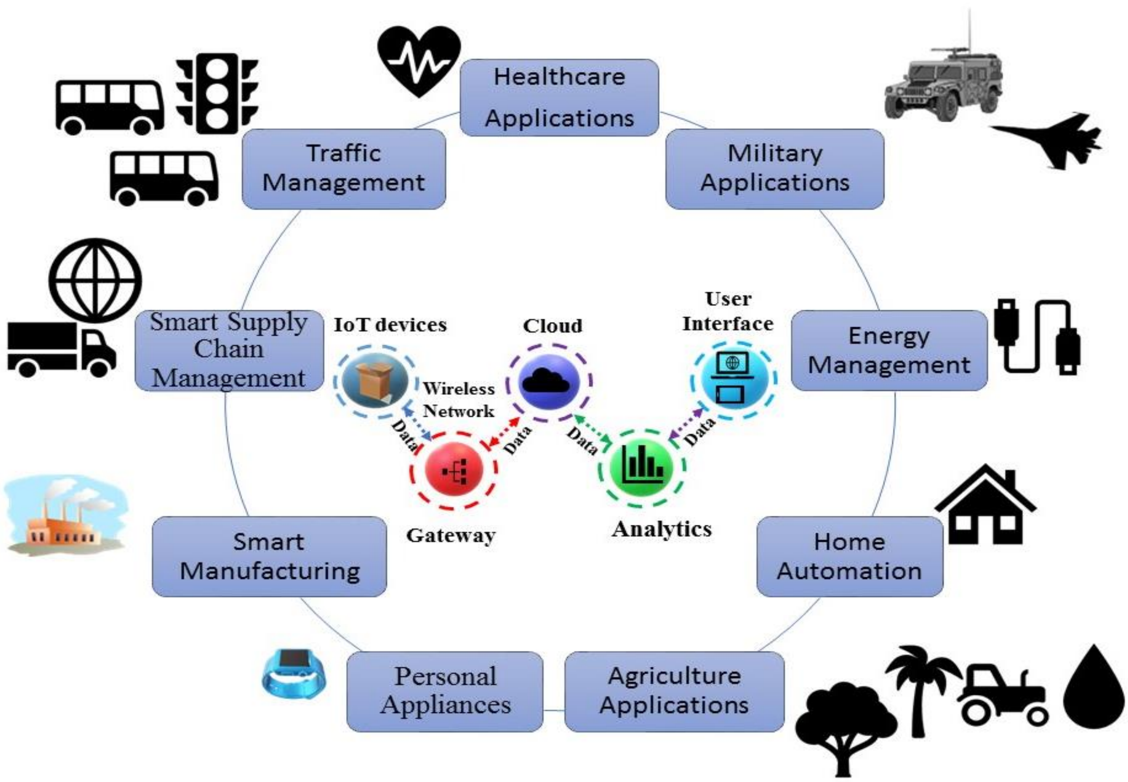


Figure 2-1: IoT ubiquitous network architecture with examples of its applications.

2.2 IoT Enabling Technologies

In principle, IoT has been established depending on other technical concepts: RFID, WSN, M2M and cloud computing as shown in Figure 2-2, the ones related to our work are briefly described here [16]:

1- WSN: Wireless Sensors Network is a wireless network that interconnects an enormous number of distributed autonomous sensors that aim to control and observe systems or environment. It characterised by its low-cost, energy efficiency, wide distribution, and self-organization properties, therefore, it is widely used [17].

2- Cloud computing: it is a service provider in a network application mode, it offers service regarding network scale and needed demand. Cloud computing comprises three models of service (as explained later in this chapter): Infrastructure as a Service (IaaS), Platform as a Service (PaaS) and Software as a Service (SaaS). Typically, the cloud offers processing and storage requirements for the users through investing the resources of the internet. In the meantime, cloud computing with IoT development attracted the attention and efforts of most of researchers and corporations to simplify the difficulties of the massive data storage and computing processing that require the support of cloud computing technology.

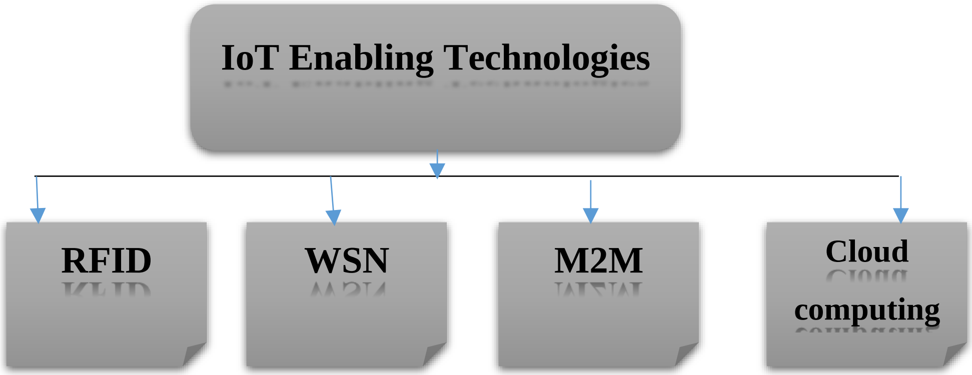


Figure 2-2: IoT enabling technologies.

2.3 IoT Elements

The main physical elements of the IoT unit are sensors and actuators, as displayed in Figure 2-3; each element has some features as explained below:

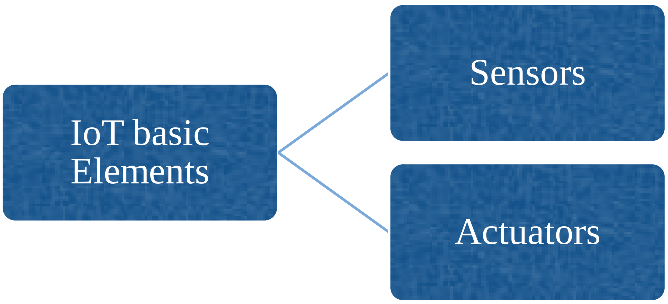


Figure 2-3: IoT basic elements.

2.3.1 Features of IoT Elements

1- Sensors: A sensor is a device that detects several kinds of input from the surrounding physical environments. The particular input could be humidity, light, smoke, heat, sound, motion, moisture, touch, pressure, or anyone of an excessive number of other environmental phenomena. The output is usually a signal that is transformed to human-readable display on the sensor site or transmitted electronically via a network for readability or additional processing [18]. A few examples of the many diverse types of sensors are as follow [18]:

1- In a mercury-based glass thermometer, the contained liquid extends and shrinks in response to the temperature, so that the input to the sensor is the temperature (i.e. detect temperature). The human can read the liquid level (high or low) from the marked gauge.

2- In a car's emission control system, there is an oxygen sensor that detects the gasoline/oxygen ratio, typically thru a chemical reaction that produces a voltage. A computer in the engine reads the voltage, and if the mix is not optimum, the balance is readjusted.

3- Motion sensors usually send out some form of energy, such as microwaves, ultrasonic waves or light beams; thus the motion is detected if the flow of energy is interrupted by objects entering its path. These sensors may be found in many systems, including home security, lights, and automatic doors.

Commonly but not permanently, the sensors have low cost, low power consumption, limited processing capability and have an interface to communicate over particular communication channel [15].

2- Actuators: Actuators can be defined as the functions of automation and control, which translate the assembled data into action orders to enhance performance automotive applications [15]. Concretely, actuators are typically mechanical or electronic devices such as switches that implement commands and orders and execute proper actions on physical things in the surrounding environment.

2.4 Communication Technologies in IoT

There are several wireless communication technologies has been integrated with IoT applications [19], as illustrated in Figure 2-4, where the Wi-Fi has been proposed to be used in this thesis :

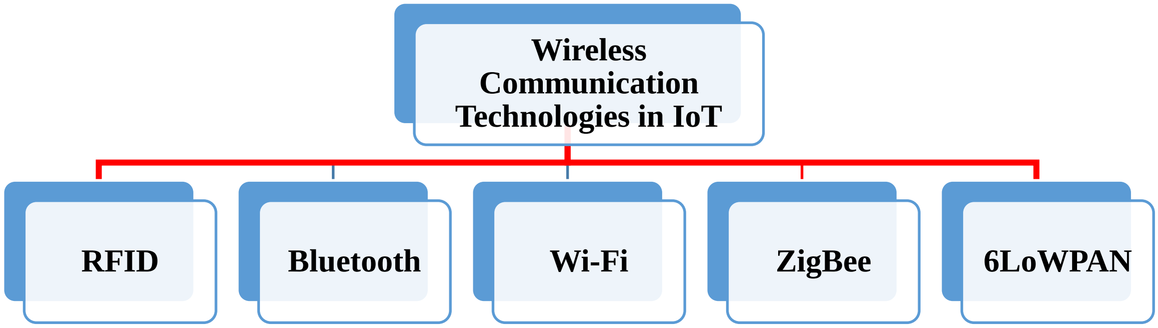


Figure 2-4: Wireless Communication Technologies in IoT.

2.4.1 Wireless Fidelity (Wi-Fi)

Principally, Wi-Fi is high speed wireless technology, that permits for multiple devices to connect over a wireless network, i.e. in wireless local area network (WLAN). Wi-Fi is based on 2.4 GHz frequency and has an IEEE 802.11 standard that has expanded to a, b, g, and n. The Wi-Fi devices have been connected to the WLAN via network access point or hotspot, with range about 50 meters for indoor. This technology extends easily by utilising multiple access points; therefore, it has been considered main broadcasting technology.

2.5 IoT Applications

IoT will impact many application topics, Figure 2.1, illustrates some of them. In this section, IoT applications have been categorised according to its domain as the following:

- Personal appliances: refers to applications where the sensors that surround us is utilised only by the individuals who directly possess devices such as personal healthcare and sport. These applications could be centralised in the cloud or local application [17]. Currently, the smartphone has been utilised as a communication gateway for several connections like Wi-Fi or Bluetooth to connect sensors measuring physiological parameters. With the increasing range of IoT personal products, innovated efficient low power solutions for the wearables appliances were provided by many industries, such as entertainments, fitness, smartwatch and tracking location.

- Home Automation: Home automation system is created through the embedding of IoT in home devices that connected by private area network, thus by using the simple application the user can monitor, operate and control their homes. For example, access control, light & temperature control, energy efficient optimisation, predictive maintenance, and connected appliances [20].

- Environment Applications: in these applications, the sensors collect data from different zones, and time to be analysed by specialists or released socially where the information is collected and forwarded to data centres. One of the main IoT application is a smart environment that is presented by the embedding of the sub-system that characterised to sense/act on one or more part of the environment [21].

- Medical and healthcare systems: Novelty of IoT devices is considered the main reason for remote health monitoring and medical emergency systems. These individual sensors could be installed within the area of eldest people or patient in anywhere, even wearable small devices such as blood pressure, heart rate monitors to advanced devices like a pacemaker. That will be guaranteeing proper treatment and help required is being directed at any time, and anywhere they are being [22].

- Manufacturing: The ability to monitor/control devices are exploited in the manufacturing IoT applications. They depend on sensing technologies to detect and read an entity’s information and collect this information to predict status and performance to deliver industrial information and services such as quality and precision demands. As IoT is developing, real time connections can be recognised as feedback between a quality monitoring system and product line system [23].

- Logistics and Supply Chain Management: The logistic work requires updating reports of tracking, such as the time and location of shipments. The IoT sensors/reader scans the tags of barcode or RFID, then send this data to the logistic data centre. The data is transmitted through many wireless communication technologies such as WSNs and global system for mobile communications (GSM) network. [17].

- Transportation: These applications support the driver in terms of selection of highways, traffic jam avoidance, find an empty parking space, in addition to the security of road. These IoT applications are not only important to road monitoring only, but these applications are also considered as an economic application by reducing fuel consumption [24]. Many of the governments have sponsored researches on IoT traffic systems to monitor the performance of their transportation.

2.6 IoT Architecture

IoT architecture is considered as a 3-layer structure which consists of the perception (sensing) layer, the network layer and the application layer [25-28].

Perception Layer: It is located in the first layer of the three-tier technology architecture. Perception layer main role is to achieve information collection, capture and recognition about things. This course of action is based on different sensing devices like a camera. Along with, this layer is in responsible for converting the sensed data into digital signals, i.e., analogue to digital conversion technique.

Network Layer: it is the second layer, its equivalent to the human nerve and brain and is mainly responsible for data transmission (routing) to various IoT nodes and other devices through the Internet. It is responsible for processing information obtained by perception layer and passing processed information to the application layer through several network technologies such as Local Area Networks, wide area network, wired or wireless networks. It selects the transmission media like WiFi, Bluetooth, 3G and Zigbee. It has the charge to perform the cloud computing and fog computing platforms, switching the devices, Internet gateways, routing devices.

Application Layer: It is an interface between the IoT and users such as people, organizations and other systems. It is responsible for material handling and for performing information storage and decision-making for all kinds of IoT applications. The application layer receives data processed by the lower layer and constitutes the front end of the whole IoT system. Moreover, the network layer formed by a different of a heterogeneous network; hence, there is a different application of IoT. Therefore, some researchers analysed one more layer (Data processing layer) called service support layer lies between the application and network layer. The support layer provides the requirements of organised services at cloud, fog and edge interfaces in an integrated way by supplying seamless hierarchical reliability, availability, safety, and security features. These layers are demonstrated in Figure 2-5.

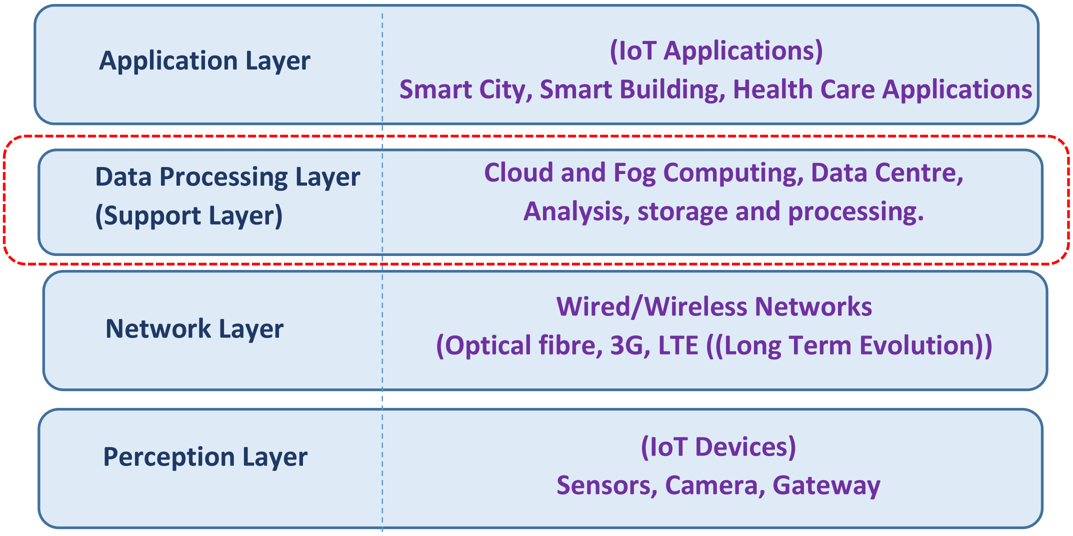


Figure 2-5: IoT Architecture Model.

2.7 Routing Technologies in IoT

The routing protocol is responsible for discovering the right route to transfer the information packet from the source node to the destination node [29]. The destination node is generally named a gateway node or a base station in IoT [30]. However, in some IoT applications, the destination node can be placed outside of the transmission range of that node. Consequently, the data packet needs to travel through multiple-hops to reach the gateway. In IoT, the sensor nodes are sensitive to energy consumption. Therefore, rigorous energy saving requirements have to comply when designing IoT routing protocols.

Routing protocols might be sorted according to the type of routing communication used within the network for transferring the data from the source to the destination. There are three types of protocols in this sorting: proactive, reactive, and hybrid. In proactive (table-driven) routing protocols, the nodes evaluate all the paths and maintain a list of destinations before the gateway communicates with the nodes in the network. Nevertheless, in reactive (on demand) routing protocols, the nodes determine a path on demand, only when the gateway requires data from the nodes by flooding the network with route request packets. Hybrid routing protocols are a combination of both proactive and reactive protocols. It is presented to decrease the control overhead of proactive routing protocols and also reduce the latency produced by route discovery in reactive routing protocols. In IoT, in the situation of static nodes, the proactive (table-driven) routing protocols are regarded the most suitable, as they use less energy than reactive (on demand) routing protocols [31].

On the other hand, paper [32] sorted routing protocols according to the network structure or on protocol operation, and this sorting is illustrated in Figure 2-6. As regards to the network structure, routing protocols can be categorised into flat routing, location-based routing, and hierarchical routing protocols. Concerning the protocol operations, there are five sub-classifications: multipath-based, query-based, negotiation-based, QoS-based, and coherent-based routing.

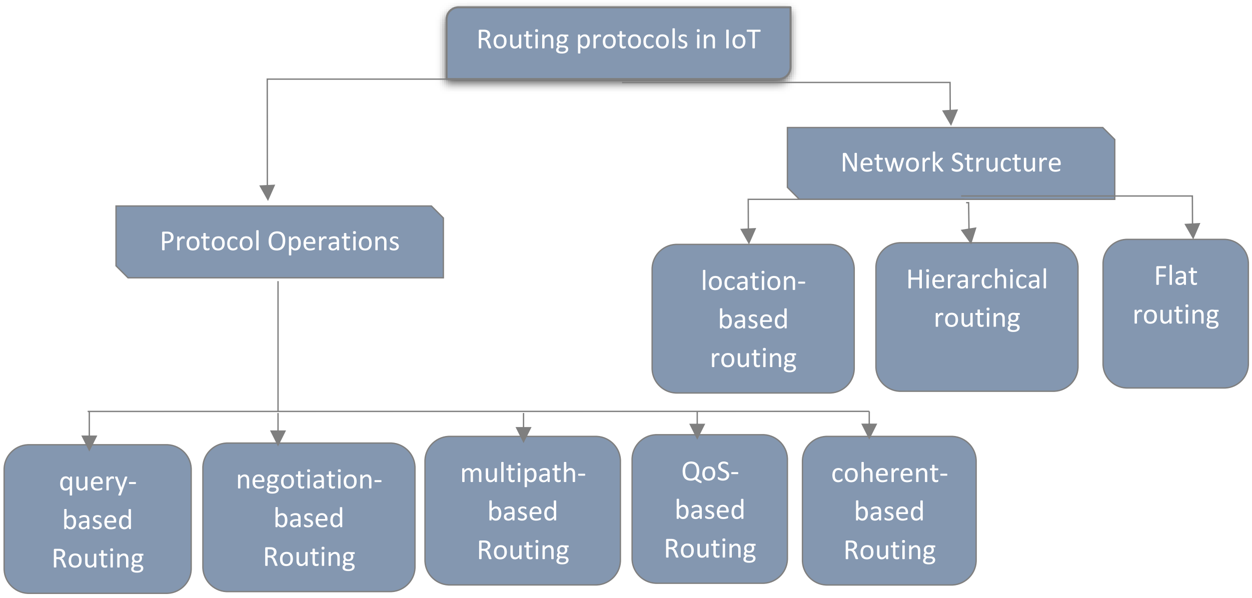
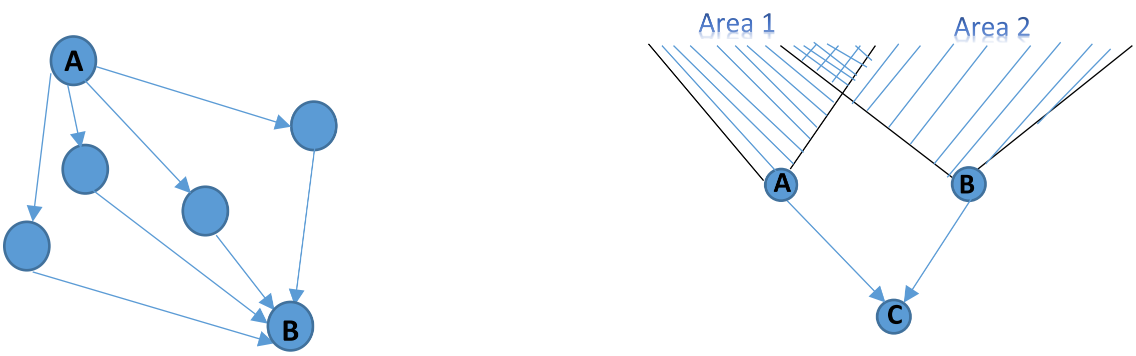


Figure 2-6: Categorization of routing protocols in IoT.



(a) Duplication of data (b) Overlapping of data

Figure 2-7: Main problems with flooding protocol.

2.7.1 Based on Network Structure

Flat network routing: In the flat-based routing protocol, all the sensor nodes act an equal task, but it is difficult to give a global identifier ID to many sensor nodes. This matter has driven the formation of data-centric routing, in which the basic idea is that the gateway broadcasts request enquiries to the whole network to retrieve data about events, without accounting the topology or the structure of the network [33]. Each node that receives the inquiry will repeat the same process of broadcasting, as shown in Figure 2-7 (a). The flooding technique is typically used in this category to convey the data through the network. Though flat routing protocols have several critical problems. One of the problems is the duplicate of data when the same packet is sent more than once to the same node. Another issue is the possible overlapping that can happen when several sensor nodes have overlapping sensor regions transmit the same data to the same neighbour. That is shown in Figure 2-7 (b), where Node C signposts the overlapping problem [34].

Hierarchical cluster routing: The main idea of the hierarchal routing protocols is to divide the IoT network into a group of nodes called clusters in levels, and each cluster is assorted by an elected leader node named the cluster head (CH), as shown in Figure 2-8. The node with the highest amount of energy can process and transmit the data, and the nodes with the lowest-energy can perform the sensing in the nearness of the target. Hierarchical routing is a versatile method to decrease the total transmission power and enhance the manageability and scalability of the network. A variance of hierarchical routing protocols has been presented in this category, including Low-Energy Adaptive Clustering Hierarchy (LEACH) [33], Hybrid Energy-Efficient Distributed (HEED) [30], and Energy Efficient Cluster Scheme (EECS) [35].

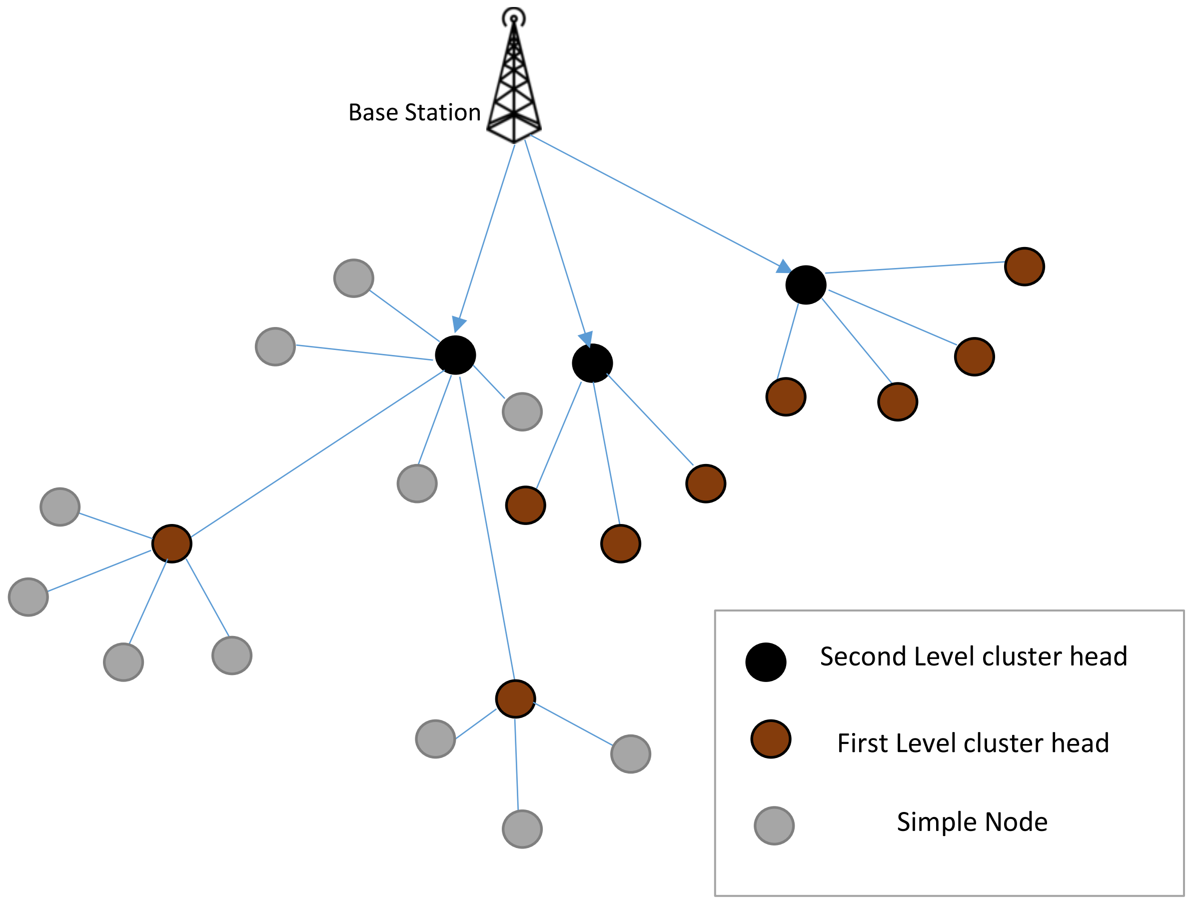


Figure 2-8: Example of a hierarchical network.

Location-based routing: The key concept of location-based routing is founded on the idea that each IoT device can evaluate the distance between their location and the neighbouring nodes within transmission ranges based upon incoming signal strength. The physical location of each IoT device can be directly deduced if the nodes are equipped with a low-power GPS receiver connected to a satellite. In location-based schemes, the IoT field is split into equal virtual grid zones to minimise the energy consumption, as shown in Figure 2-9.

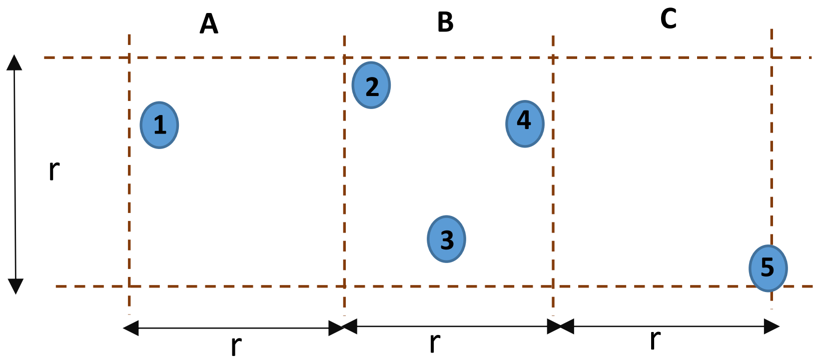


Figure 2-9: Example of virtual grid zones in GAF.

IoT devices in the same zone will have equivalent costs of routing. Consequently, some IoT devices in the same zone can be avoided by assigning them into sleep mode. Accordingly, the more nodes there are in sleep mode, the more energy is saved. Common location-based schemes involve geographic adaptive fidelity (GAF) [36] and geographic and energy-aware routing (GEAR) [37, 38].

2.7.2 Based on Protocol Operations

The IoT routing protocols have other categorizations based on certain system factors, which can be directed to adjust to existing network conditions and residual energy level. These protocols might be partitioned into the following types: multipath-based, query-based, negotiation-based, QoS-based, and coherent-based protocols [33].

Multipath-based: Multipath routing protocols enhance network performance by using multiple paths routing rather than single path routing. There is constantly an alternative path between the source and destination as an alternative in the situation of the primary path failing. Retention alternative paths would boost network reliability, while correspondingly increasing overheads. An example of this form of routing protocol is directed diffusion [30].

Query-based: In this routing type, the gateway sends enquiries to IoT devices in the network. The IoT device that is detecting and collecting data matches the one demanded in the enquiry, transmits the data back to the demanding node or to the gateway. The Active Query Forwarded in Sensor Networks (ACQUIRE) is a type of the query routing protocol [39, 40].

Negotiation-based: The negotiation-based protocol uses high-level descriptors for data utilization to omit redundant data transmissions throughout nodes. In the flooding method, the same data content is sent or interchanged several times between the same nodes, and this induces the reception of duplication copies of data by sensor nodes. Hence, overlapping and collisions occur during transmissions, where much energy is consumed throughout the process. The prime motive of negotiation-based routing protocols is to avoid duplication information being forwarded to the next nodes or the gateway, by using a succession of negotiation messages before transmitting the data [29, 41]. The Sensor Protocols for Information via Negotiation (SPIN) family of protocols are types of negotiation-based routing protocols.

Quality of service (QoS)-based: The core notion in this type of routing protocol is that the network must balance energy efficiency and QoS. Whenever the gateway requests data from the IoT devices in the network, the communication needs to satisfy QoS demands, for instance, delay, energy consumption, and bandwidth [32]. The Sequential Assignment Routing (SAR) presented in [42] is the early IoT routing protocol to introduce the notion of QoS in routing decisions. The SAR routing choice is subject to three metrics, precisely, amount of the remaining energy, QoS on each path, and priority level of each packet to avoid a path breakdown within the network.

Coherent and non-coherent-based: The main task in the IoT process is data processing. Routing protocols use diverse data processing techniques during the gathering and transmission of the data within the network. This sort of protocols can be classified into two types of data processing techniques; coherent and non-coherent [43]. In coherent routing, the data is sent to aggregators after minimum processing. The minimum processing typically comprises tasks like timestamping and replica suppression. Coherent processing is usually nominated to achieve energy-efficient routing. In non-coherent data processing routing, IoT devices will locally process the raw data before sending it to other IoT devices for additional processing. IoT devices that complete additional processing is named aggregators IoT devices or CH.

2.7.3 Neighbour Discovery Protocol (NDP)

The scale of the internet is growing fast, particularly on the user side where the number of internet-enabled mobile devices rises rapidly, this means that an enormous number of IP address allocation required, for the connected devices, which seems impossible to satisfy with internet protocol version 4 (IPv4). Therefore, it is expected that internet protocol version 6 (IPv6) will be popular and soon replace IPv4. The motivation behind the formation of IPv6 was to tackle the requests of IPv4 address attrition [44]. IPv6 is developed as the next-generation network layer protocol, its 128-bit address format significantly enlarges the address space and will satisfy the address demands for a fairly long time. The internet protocol was modified in IPv6 to address the unexpected development of the internet. Neighbour discovery protocol (NDP) is the primary protocol of the IPv6 suite; the purpose of NDP is to substitute address resolution protocol (ARP), router discovery, and redirect functions in IP4. NDP is defined as the stateless protocol because it is used by the IPv6 nodes to specify joined hosts in addition to routers in an IPv6 network deprived of the need of dynamic host configuration protocol server. Several serious functionalities can be managed with NDP. For example - specifying nodes on the same link, revealing link-layer addresses, detecting replica addresses, looking for routers, and conserving reachability information concerning paths to an active neighbour [45].

2.8 Interference in IoT system

A significant threat to the reliability and energy efficiency of low-power wireless networks used in the IoT is radio interference.

2.8.1 Energy Efficiency

Interference happens during the transmitting and receiving packets on the same frequency. Therefore, it increases the probability of packets collision and reduces the performance of wireless communications. That will affect the quality of service parameters such as throughput, delay, reliability, and contributes further to the power depletion in the nodes [46], which greatly reducing the energy transmission efficiency. It is important to control the interference generated by mutually interfering data streams, some of which may transport information critical to accomplish real-time IoT computational tasks [47]. In general, a wireless device always associates itself with the base station that provides the strongest desired signal. An interference signal from another base station downlink or another device uplink is always received at lower power than the desired signal due to the long communication distance or low transmission power. However, the interference signal could be stronger than the desired signal. That may lead to the degradation of network throughput due to a reduction in the link rate if the resources in the network are not reasonably allocated to links [48]. In our work of **chapter 4**, a minimum transmitted power level is defined to control the interference so that the QoS of users can be guaranteed due to the low interference strength from IoT devices transmitters.

2.8.2 Reliability

Within a large IoT network, with multiple sensing nodes operating simultaneously, the signals transmitted by the neighbouring sensing nodes interfere with each other, the presence of interfering signals severely deteriorates the reliability of the IoT. The problem of interference is required to be addressed to achieve reliable surveillance.

2.8.3 Multi-channel Approach

A multichannel approach helps to reduce the number of packet retransmissions and losses, thus giving more energy efficient usage during communications (less energy waste). By using multichannel communication in wireless networks, the effects of interference can be mitigated to enable the network to operate reliably and improve the network efficiency, stability and, minimise latency and overall energy consumption. Routing scheme of the IoT network considers the benefits of routing over multiple channels, which can further improve the network’s energy usage while maintaining a high rate of successful communications. The multi-channel approach is applied in **chapter 3** and **4**.

2.9 Overview of Cloud Computing System

Cloud computing is a type of internet based computing that share the processing, storage resources and data via different devices (computers, mobile phones, tablets, laptops) on demand. This sharing model provides ubiquitous on demand access to the computing resources such as networks, servers, storage and applications. Cloud computing offers variant capabilities to the users and companies to process and store their data in the data centres as a third party [49]. Moreover, cloud reduces corporation's infrastructure costs and allow the running of the applications faster with enhanced manageability and less maintenance, furthermore, adjusting the resources (software, hardware, network and required services) to meet the commercial demand would be rapid and flexible [50]. Some factors that led to the development of cloud computing such as networks of high capacity, low cost storage devices and computers in addition to the extensive trend to adopt hardware virtualization and autonomic computing. As a result, many advantages could be obtained from cloud computing, for instance, dynamic scaling, fewer capital expenditure (CAPEX), high availability, easy to manage, shared resources, low-priced cost of services, high performance, accessibility, high productivity (high computing power), reliability, increased mobility and friendly to the environment. These benefits made cloud computing greatly demanded service [51].

2.10 Development of Cloud Computing Technology

The fundamental notion of cloud computing was presented in the 1960s by John McCarthy. He believed that in the future computation may be systematised as a public service [51]. Moreover, the cloud computing characteristics were examined in 1966 for the first time by Douglas Parkhill, the author of (The Challenge of the Computer Utility) book [52, 53]. The invention or history of the term cloud is from the telecommunications world, where telecom companies (providers) began offering virtual private network (VPN) services for data communication with comparable quality of service at a considerably lower cost. Through using VPN services, they can switch traffic to balance employment of the overall network. Also, in previous, the term cloud has been utilised to denote the platforms for distributed computing, parallel processing and grid computing [54]. Cloud computing today expand to cover servers and network infrastructure. Many companies in the industry have attracted to cloud computing and executed it. Amazon played a key role wherein 2006, the Amazon web service (AWS) was launched. Also, Google and international business machines corporation (IBM) have initiated research projects in cloud computing. For instance, Eucalyptus is an open source platform for using private clouds [55].

2.11 Literature Review

The literature review related to this thesis is provided for different topics that are energy efficiency and reliability besides to MILP based related work. Literature review of **chapter three** is presented first, then **chapter four** and finally, **chapter five**.

2.11.1IoT Challenges

2.11.1.1 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. Some critical issues regarding the reliability of IoT are discussed below.

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 [56]. 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 cannot 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 the cloud may face failures or losses, owing to several factors; for example, traffic congestion or interference [57], [58].

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 [59]. When there is not enough storage space to store the sensed data, then the cloud cannot attain any sensory data. That can happen even if the IoT devices have enough residual energy to collect and transmit data and the transmission to the cloud is successful. In this chapter, it has been assumed that sensors have sufficient storage space.

- In **chapter three**, a reliability model is proposed for cloud based IoT network that is able to provide target reliability in the presence of interference without causing a higher level of power consumption. However, related works 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 sensor node reliability and energy efficiency. The related researches are as follow:

Many published papers discuss the problem of reliability, considering energy efficiency. In paper [60], they consider the problem of deploying WSN that meets a specified minimum level of reliability during its mission time at a minimum network deployment cost. An ant colony optimisation algorithm coupled with a local search heuristic was proposed as a solution to minimise the internal interference, bandwidth usage and energy consumption throughout the network's mission time. In paper [61], 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) optimisation scheme was proposed. In paper [62], 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 [2]. It involves two parts: 1) 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

[63], 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 [64], 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 [65], 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 includes: In this work [66], they present 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 [60], they consider the problem of WSN reliability while minimising internal interference throughout the network's mission time.

Paper [67], 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 [68] 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 [69] 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 [70], 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 [71], 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 a 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 [72], 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 [73], a highly 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. Also, it tolerates the maximum number of dormant and malicious faulty components in the IFCIoT platform.

2.11.1.2 Energy Efficiency

IoT is 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. This thesis is focusing on methodologies that have been minimised the power consumption of the IoT integrated with cloud computing. Where through those tools, the IoT operators can reduce their power consumption. These methods can keep the same level of performance with low installation budget.

- **The following related work is focusing on the different methodologies that have been proposed for minimising the power consumption of IoT systems with a demonstration of the differences from our work of chapter four.**

Researches of energy efficiency in of IoT systems integrated with cloud computing: In [74], they present a heuristic and opportunistic link selection algorithm, HOLA, that would minimise the overall energy consumption besides to balance the energy across the industrial IoT network. These smart-devices with multiple radio links like Bluetooth, WI-FI, and 3G/4G Long-Term Evolution (LTE) heuristically specify the best link to transmit the data to the cloud according to the quality and energy cost of the link. Energy-efficient architecture for IoT has been proposed in [75], that entails three layers: sensing and control, information processing and presentation. This architecture enables the system to predict the sleep interval of sensors according to their remaining battery level, their previous usage history and quality of information required for a specific application. The predicted value can be utilised to increase the use of cloud resources by providing the allocated resources when the corresponding sensory nodes are in sleep mode. The authors in [76], deal with high energy consumption problem by proposing a higher energy efficiency reduced hardware architecture system-on-chip targeting digital block design. In this work [77], they have presented Torpor. This power-aware hardware scheduler allows IoT nodes to efficiently execute part of their applications using irregular harvesting power, while still guaranteeing their always-on required functionality with a battery. In [78], they propose an IoT framework with smart location-based automated and networked energy control. The framework utilises a smartphone platform and cloud-computing technologies to allow multiscale energy proportionality. It includes building-, user-, and organizational-level energy proportionality. Paper [22], suggests a polynomial-time algorithm for energy-efficient dynamic packet downloading from medical cloud storage to medical IoT devices. The algorithm calculates the amount of power allocation in each access point based on the buffer backlog size and channel states under the consideration of buffer stability. Through the suggested adaptive algorithm, each access point adjusts its parameters for more adaptive power/energy management. In paper [79], they present a context-aware, specifically, location and activity-aware mobile sensing platform called context-aware mobile sensor data engine (C-MOSDEN) for the IoT domain. C-MOSDEN successfully minimises energy consumption, network communication requirements, and storage requirements. In paper [80], they propose an original media access control (MAC) scheme for energy efficiency in wireless smart sensor networks. They presented a technique provides better performance in terms of energy efficiency by grouping wireless smart sensor devices and reducing the energy consumption of the smart sensors according to buffer threshold values which are pre-configured based on the distances from the sink node. The suggested technique comprises priority control for supporting emergent traffics. In [81], they proposed a virtual CH election scheme (VCHEC) that delivers an energy-efficient clustering algorithm and investigates CH distribution in WSNs. Nodes do not need to transmit data to a faraway CH and lead to energy inefficiency. Furthermore, in VCHEC, they suggested an energy efficient CH election mechanism, which can select a node with higher residual energy. In this research [82], their primary contributions include cloud-based services for monitoring the tradeoff between the data quality (DQ) and energy consumption of the sensor. This architecture adjusts to DQ needs and a producer/consumer data stream best matching cloud service. This paper [83], has presented a middle layer named an edge computing layer to reduce latency in IoT. They have planned to decrease the energy consumption of a mobile device in addition to the energy consumption of the cloud system whereas encountering a task’s deadline, through offloading the task to the edge datacentre or cloud. They propose an adaptive technique to optimise the energy consumption and latency by offloading the tasks and as well by choosing the suitable virtual machine for the implementation of the task. Paper [84], 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 minimised, thereby saving energy. In [85], they introduce an optimally energy-efficient VM selection and migration approach for IoT in the cloud environment. They manipulate the task classification, task assignment issues, VM selection and allocation mechanism, to decrease the number of active physical machines. That results in accurate service provisioning, maximisation of resource utilization and a reduction in the number of VM migrations while ensuring achievement of service level agreements guarantees. Hence, they introduce an energy-efficient resource ranking and utilization factor-based virtual machine selection approach by taking into consideration the comprehensive resource balance ranking scheme, processing element cost function, energy consumption model and resource utilization square model. In this article [86], an emphasis on how to improve the energy efficiency of edge caching using in-memory storage and processing is presented. They build a three-tier heterogeneous network structure and assume two edge caching methods using the diverse time to live designs and cache replacement policies. In this paper [87], they propose a cognitive data delivery (routing) protocol that addresses the challenges of data delivery in IoT networks comprised of energy-constrained IoT sensors. They consider the entire network energy while choosing the next hop for the routed packets in the targeted WSN. In paper [88], a low power, energy efficient communication protocol is proposed. The described protocol optimises how 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. The proposed model in [89] combines the prediction scheme in the cloud system and load balancing routing approach in a sensor network to minimise energy consumption. There is less communication between the sensor network and cloud computing compared to traditional sensor cloud models. In [90], they present a software defined networking (SDN)-based edge-cloud interplay to deal with flow scheduling among edge and cloud devices. Wherein SDN provides efficient middleware support. They evaluate the proposed scheme for two optimisation problems: trade-off between energy efficiency and latency, and Trade-off between energy efficiency and bandwidth. Energy consumption of nano data centres(nDCs) for IoT was studied in [91], where they propose and utilise flow-based and time-based energy consumption models for shared and unshared network equipment, respectively. They made a comparison between the energy consumption of applications utilising centralised DCs in cloud computing and those deploying nDCs employed in Fog computing.

- The works mentioned above involve concentrating on how to maximise 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 **chapter 4**. That is done using location and function criteria of the nodes.

In addition to that, some works have addressed the energy-efficient routing problem in an IoT network. In [92], the authors proposed an energy aware ant routing algorithm (ARA) for IoT. They delivered new mechanisms for estimating the fitness of a path and energy information dissemination, thereby allowing for the prolonging the network lifetime. The ARA favours shortest paths over others, and they extended it with an energy heuristic for specifying the nodes' residual energy and a scheme for estimating that of a path. Two new routing protocols for the underwater wireless sensor networks was proposed in [93]. The presented schemes significantly improve the network performance in terms of delivery ratio, energy expenditure and delay. Paper [94] introduce an energy efficient ring routing protocol with a mobile sink for wireless sensor network. This protocol uses a hierarchical architecture which reduces the energy consumption of the network. Modified Balanced Energy efficient network integrated super heterogeneous algorithm is proposed in [95] to elect a CH. It provided efficiency in terms of a node's lifetime, throughput, reduced delay and reduced energy consumption. In [96], they classify the industrial sensed data into three kinds, high timeliness event data, low timeliness event data and periodic data. They propose an energy efficient and QoS Aware routing algorithm. A different routing strategy routed the different types of data packet. In this paper [97], they study the QoS routing of WSN. They propose a distributed learning automaton based algorithm to provision the QoS requirements for packet routing in WSNs. In terms of energy efficiency, their method tried to select the best possible nodes to save other nodes' residual energies. It used a small number of sensors with high-reliable links to transfer information of a particular event in a network. Their algorithm achieved a good balance among multiple QoS constraints such as end-to-end delay and energy consumption.

- In these works, although they proposed different schemes for hops minimisation to achieve energy efficiency, none of these contributions considers further transmission power reduction of the network based on fading sub-channel gain.

Some research has involved exploiting the channel state information to achieve energy efficiency. Paper [98] study the dynamic channel accessing problem to improve the energy efficiency in clustered cognitive radio sensor networks. Moreover, two sequential channel sensing and accessing schemes have been proposed for intra- and inter-cluster data transmission, respectively. The proposed schemes reduced the energy consumption of data transmission significantly. In [99], digital and analogue transmission energy planning algorithms were presented for progressive estimation in multi-hop sensor networks. The routing tree and channel state information of the WSN was exploited to reduce the network transmission energy while ensuring pre-specified estimation quality in a finite time. A general formula was derived for the lifetime of WSN. In [100], they formulate an optimisation problem to solve the unbalanced energy consumption problem in the orthogonal frequency division multiplexing (OFDM) system for a WSN. The effect of the number of subcarriers and sensor nodes on the fairness were studied in the numerical simulation. The proposed method improved the sum throughput performance and simultaneously preserved the energy consumption fairness among all the sensor nodes. Paper [101] investigate a computation offloading management problem for IoT in a heterogeneous network to minimise the network-level energy consumption. To achieve the best energy efficiency for all users, they formulate an energy minimisation problem by jointly considering heterogeneous computation resources, latency requirements, power consumption at end devices, and channel states information. Paper [102], presents the analytical model of the energy transmission channel for the resonant beam charging (RBC) system, and study how long distance RBC can reach and how much power RBC can transfer in theory.

Other works have involved using the multi-channel approach to deal with the interference issue as in paper [103]. They analyse the adjacent channel interference (ACI) effect on WLANs in IoT network and propose an interference-aware self-optimising (IASO) Wi-Fi design that incorporates a multi-channel multi-level carrier sense and adaptive initial gain control scheme. In this paper [106], a logical link-based partially overlapping channels interference model is analysed to mitigate the inter-channel interference, and a channel selection scheme is formulated as a potential game.

- However, the above works have been focused on using sub-channel approaches and channel state information either for interference cancellation or energy efficiency, thus having not taken advantage of them to reduce traffic power and interference together, as suggested in our work in **chapter 4**.

- Overall, in related works, although they proposed different schemes to achieve energy efficiency or interference cancellation, nevertheless, none of these contributions consider combining these schemes to attain the two objectives. Differently to these approaches, in **chapter 4**, cloud technology with our proposed network architecture have been used for hops minimisation and fading sub-channel gain selection optimisation to realise energy efficiency and interference elimination together using MILP programming tool.

- **Researches that are related to our work in chapter five, which include achieving energy efficiency through adaptive data compression techniques:**

1- Adaptive data compression: The authors in [104] propose a system that uses the surplus energy to compress data and expand transmission range in energy-harvesting WSN. An energy-adaptive data compression scheme was proposed in [105] to control the sensing rate in an energy-harvesting WSN. In the proposed scheme, by depending on the remaining energy of the node, each node can adjust the data collection period (to increase accuracy) and select the sensing rate without any rise in blackout time. In paper [106], nodes with surplus energy less than a specific threshold compress data before transmission to reduce energy consumption. While nodes with surplus energy over the threshold (which means there is surplus energy) transmit data without compression in order to decrease the delay time (latency) between nodes. In [107], they introduced a dynamic network selection mechanism that permits energy efficient and high quality patient health monitoring via targeting, together, radio access network selection and adaptive data compression. In this paper [108], energy efficient data reduction scheme for IoT-Edge applications was proposed. They apply a fast error-bounded lossy compressor on the collected data prior to transmission. They rebuild the transmitted data on an edge node and process it using supervised machine learning techniques.

2- Data compression algorithms for IoT to span network lifetime: in paper [109], a tree-structured linear approximation scheme is proposed to compress sensing data, according to an optimal rate-distortion (R-D) relationship. A novel data compression scheme is presented in [110], which enables a hybrid transmission mode for balanced data quality and power consumption. The proposed scheme encodes the raw data using a lossy technique, and the residual error from reconstruction is coded for lossless restoration. The goal of paper [111] is to develop a new coding scheme for delta compression as a technique for energy saving in an IoT environment. It is designed for applications where the sensor measurements are not needed in real-time. Paper [112] presents a two-tier data reduction framework: The Dual prediction scheme is used to reduce transmissions between cluster nodes and cluster heads, while the data compression scheme is used to reduce traffic between cluster heads and sink nodes. In this paper [113], they have presented a fog-based optimised Kronecker-supported compression scheme that can achieve better compression results and reduce energy consumption in Industrial IoT (IIoT). In this work [114], they present a dynamic time division multiple access-based scheduling scheme that jointly considers energy consumption and data distortion. They study the tradeoff between lifetime and distortion and set up a framework that allocates the energy in every frame, determines the compression of the data to send along with the transmission durations, and performs power control. In this study [115], they present a data compression algorithm with error bound guarantee for WSN using compressing neural autoencoder networks. The proposed algorithm reduces data congestion and reduces energy consumption by exploiting spatiotemporal correlations in the training data to generate a low dimensional representation of the raw data. The adaptive rate-distortion feature balances the compressed data size (data rate) with the required error bound guarantee (distortion level). In [116], Grade diffusion (GD) algorithm along with the LZW compression technique used to increase the overall network lifetime. Where grade diffusion algorithm selects the more available energy node as the relay node in the routing process.

Furthermore, the LZW algorithm minimises the transmitting and receiving power by compressing the original data size. In this letter [117], they explore the use of autoencoders as an efficient and computationally lightweight way to lossy compress biometric signals. Although the presented techniques can be used with any signal showing a certain degree of periodicity, in this study they applied them to ECG traces, displaying quantitative results in terms of compression ratio, reconstruction error and computational complexity.

- In the literature, they have been using data compression to mainly focus on: increase accuracy, reduce latency, minimise distortion level, span network lifetime and modifying more robust data compression techniques. The model has been developed to achieve energy efficiency. However, it should be clarified that the model developed here in **chapter 5**, differs from the existing ones in the following aspects: Firstly, our energy efficiency model focuses on minimising total network power consumption contributed by various network components such as sensors and routers. Secondly, in our energy efficiency model, in addition to the battery level, the processing capability of the IoT devices is considered.

- The **MILP-based literature** related to our study includes: Paper [118], proposes a framework for an energy efficient cloud computing platform for IoT along with a passive optical access network. The design is evaluated using the MILP model; the energy efficiency is achieved by optimising the placement and number of the mini clouds and Virtual Machines and utilising 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 optimising the selection of IoT nodes and routes in the IoT network to meet the demands of the business process virtual nodes and links to minimise the IoT system total power consumption. In [119], 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 optimised to minimise the energy consumption of the processing and networking equipment. In this paper [120], 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 optimisation framework, aiming to minimise the electricity cost required to satisfy the scheduled load demands. This research [121], implemented an automated real-time Heating Ventilation and Air Conditioning (HVAC) control system on top of an IoT framework, based on a thermal comfort optimisation problem, demand response and majority user feedback. They use artificial neural networks to predict the thermal parameters of a room based on historical time-series data. Where they optimise the HVAC control problem using MILP for an optimal energy efficiency-user comfort trade off. In this paper [122], They present a decentralised 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-centred and QoS-aware services selection approach (EQSA) for IoT environments is presented in [123]. EQSA is formulated and solved as a multi-objective optimisation problem; this approach allows minimising energy consumption to ensure 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 optimisation 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%).

2.12 Research Methodology

Mixed Integer Linear Programming (MILP) has been used to develop and simulate all the models of this thesis. MILP is a mathematical optimisation programme in which all the bounds, constraints and the objective function are linear. That is where the linear programming terminology derived from [124]. The IBM ILOG CPLEX optimisation studio is used to solve MILP models in this thesis. AMPL (A Mathematical Programming Language) is used to access the CPLEX solver; it connects the model and its data files with CPLEX [125]. This solver ran on an i54288U CPU, 2.60 GHz, 8 GB of RAM machine, the data sets for different power consumption and evaluation parameters have been derived from real values of IoT devices datasheets, and it has been demonstrated in each chapter of the thesis.

Chapter 3

3 Energy Efficient and Reliable Transport of Data in Cloud based IoT

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, four scenarios of optimisation is presented using a mixed integer linear programming (MILP) model. First, a standby routes selection scheme (SBRS) is used to replace node failures and achieve reliability with minimum traffic power consumption. Second, a desired reliability level scheme (DRLS) is used, which minimises the traffic power consumption of IoT devices while considering the desired reliability level as a key factor. A reliability-based sub-channel scheme (RBS) is proposed to avoid overhead on busy reliable routes while mitigating interference. Moreover, a reliability-based data compression scheme (RBDS) is presented to overcome the capacity limits of the links. The results show that our proposed schemes reduce the negative effect between reliability and total traffic power consumption with an average power saving of 57% in SBRS and 60% in RBDS compared to DRLS.

3.1 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 utilise 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, analyses, 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 a network connection. In these potential applications of cloud based IoT integration, such as smart buildings in smart cities [126, 127], a number of them require the IoT to reliably offer sensory data to the cloud, based on the requests of the users [128]. 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 [5]. A number of approaches have been evolved to optimise 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 [67] 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 traffic power consumption. In this work, it has been considered that the IoT network can fail in two points: links due to traffic congestion or interference and sensor nodes due to diminishing their energy. This chapter 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, the following approaches are used: first, each model has the objective of minimisation 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, two approaches are proposed; 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 optimisation objectives: energy efficiency and reliability.

The main contributions of this chapter are summarised as follows:

• Virtualize cloud based IoT network using MILP model.

• Minimise the total traffic power of the cloud based IoT network through MILP optimisation model.

• Minimise interference.

• Achieving reliability in the cloud based IoT network.

• Distributing traffic through the gateways to avoid traffic congestion to the cloud in the IoT network.

• Handle more traffic demands by using a data compression technique.

• Investigate jointly the issues regarding energy efficiency and reliability from the viewpoint of cloud based IoT integration.

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

This chapter further proposes four schemes consisting of a standby routes selection scheme (SBRS), the 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, an SBRS is used to selectively choose standby routes to overcome node failure problems and reduce transmission power. Besides, a DRLS is used when a specific reliability level is needed to guarantee the link reliability while minimising transmission power. Furthermore, an RBS uses sub-channels to mitigate interference and reduce overhead on links that are utilised 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.

3.2 Overview of S-LEC Data Compression

Power consumption is a critical problem affecting the lifetime of IoT networks. Several 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 a few bits, which leads to a minimisation in the required inter-node communication, which is the main power consumer in the IoT. That 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) [146]. 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. Data compression techniques are explained in detail in **chapter 5**.

3.3 Cloud based IoT Integration System Model

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

It is supposed that there is a real-world scenario of smart buildings in a smart city with multiple user applications [126, 127], 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 analyse these data to satisfy the data requests from each corresponding user.

Cloud computing offers a platform as a service, through which the users can run, manage, and develop their applications. An example of the 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. 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 Figure 3-1, and it consists of three layers [129]:

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 enormous volumes. To extract interpretable information from these data, they have to be stored, processed, and analysed. 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.

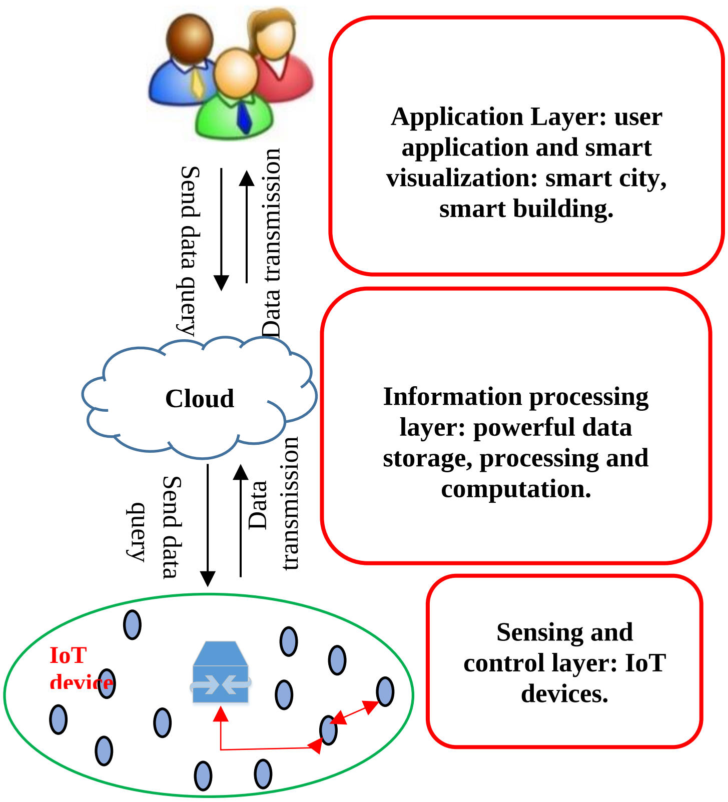


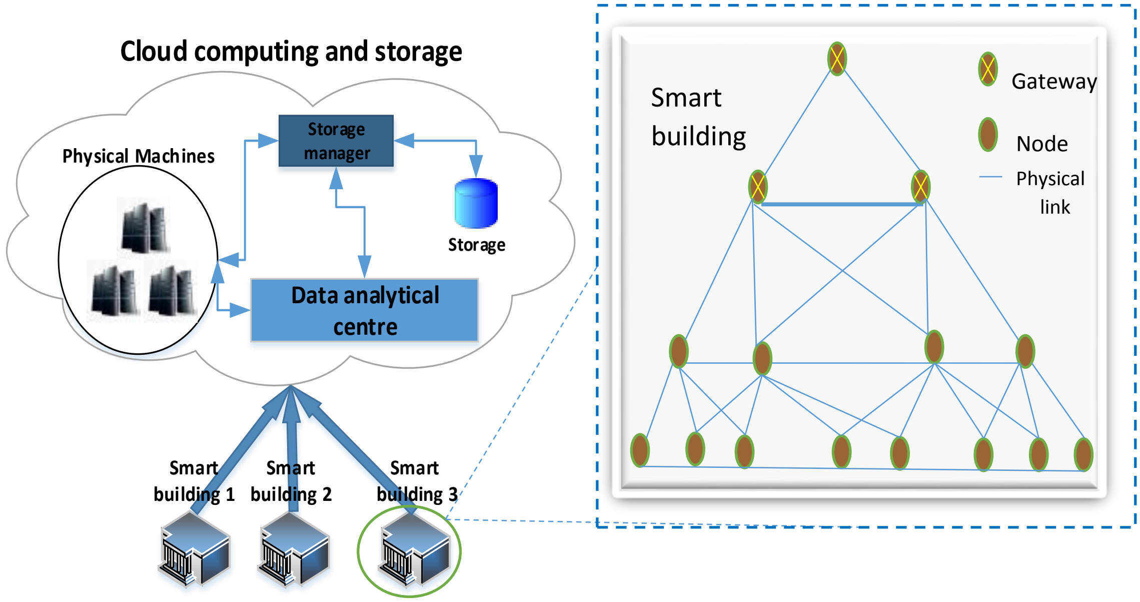
Figure 3-1: Architecture of cloud based IoT network.

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 have different protocols for communication.

3.4 Network Optimisation Model of Cloud based IoT

Our mathematical model is developed using mixed integer linear programming (MILP), which is mathematical programming that can perform optimisation of a function of many variables subject to constraints. As clarified above, a cloud based IoT system is supposed.

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 Figure 3-2 (a).



a) Physical network of a smart city

b) Topology of one of the smart buildings in the proposed IoT network of a smart city.

Figure 3-2: a) Physical network of a smart city and b) Topology of one of the smart buildings in the proposed IoT network of a smart city.

It is supposed that these smart buildings (B) each have four floors (F), each with a number of IoT devices. The nodes in the first and second floor of each building serve as a gateway to collect data to send to the cloud, as explained in Figure 3-2 (b). Each IoT device is linked to their neighbours 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 Figure 3-2 (b), in which neighboured sensor nodes can communicate with each other and relay messages between them through the network [130].

Table 3- 1: 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 neighbours of the IoT device *i*.

Table 3- 2: 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 the cloud before compression.
CP_a	The power consumed for compressing the data using the compression algorithm *a*.
CR_a	The compression ratio of the specific data compression algorithm *a*.

Table 3- 3: 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 neighbour 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.

3.5 Objectives of the Proposed Model

The objective is to integrate reliability with minimum total traffic power consumption in the cloud based IoT network with a less negative effect on each other. That is done through SBRS, DRLS, RBS and RBDS. That is accomplished by creating a parameter LK_G^d which indicates the traffic between the IoT device (d) and the cloud (G).

$$LK_G^d = \begin{cases} 1 & \text{If there is link between the IoT Device and the Cloud} \\ 0 & \text{Else} \end{cases} \tag{3.1}$$

The routing concept in this chapter is based on the flow conservation constraint for the traffic flows in the physical network by Tucker [131]. It is also explained in our previous work [132]. A binary variable $R_{i\ j}^{d\ \ G}$ is formed, which represents the route between the IoT device (d) and the cloud through the repeaters nodes *(i, j)* where *j* is neighbour of *i*.

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

$$\{\sum_{j\in NB[i]} R_{i\ j}^{d\ G} - \sum_{j\in NB[i]} R_{j\ i}^{d\ G}\} = \mathrm{LK}_G^d \tag{3.2}$$

$$\{\sum_{j\in NB[i]} R_{i\ j}^{d\ G} - \sum_{j\in NB[i]} R_{j\ i}^{d\ G}\} = 0 \tag{3.3}$$

$$\{\sum_{j\in NB[i]} R_{i\ j}^{d\ G} - \sum_{j\in NB[i]} R_{j\ i}^{d\ G}\} = -\mathrm{LK}_G^d \tag{3.4}$$

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, then it is a destination. The lists of sets, parameters and variables defined in the MILP model are briefly highlighted in tables (3-1 – 3-3).

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:

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

$$R1\,_{i\ j}^{d\ G} + R2\,_{i\ j}^{d\ G} \leq 1 \tag{3.5}$$

where, $R1\,_{i\ j}^{d\ G}$, $R2\,_{i\ j}^{d\ G}$: binary variables indicate the 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: minimise

$$\sum_{i\in D} E_i * NT_i + \sum_i T1_{i\in D} * DL_i + \sum_i T2_{i\in D} * DL_i = TPS \tag{3.6}$$

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

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

$$R_{i\ j}^{\ d\ G} * RL_j^i \geq R_{i\ j}^{\ d\ G} * 99\% \tag{3.7}$$

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

Objective: minimise

$$\sum_{i \in D} E_i * NT_i + \sum_i T_{i \in D} * DL_i = TP \tag{3.8}$$

C. *Reliability-based sub-channel scheme (RBS):* In order to avoid overhead on busy reliable routes, it is supposed that there are multiple channels for transmission, as illustrated in table 3- 4, which also reduce interference. To cancel the interference, two constraints have been adopted: First, there is only one traffic path between the device and the cloud.

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

$$\sum_{j \in NB[i], i \neq j} \sum_{c \in sch} RC_{i\ j\ c}^{\ d\ G} \leq 1 \tag{3.9}$$

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

$\forall i \in D$

$$\sum_{c \in sch} T_c^i \leq 1 \tag{3.10}$$

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), S-LEC data compression is used 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 [146], 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:

$\forall \ i \in D$

$$\sum_{a \in A} TB\,_G^i * CR_a * CI_a^i = ST_G^i \tag{3.11}$$

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

Objective**:** minimise

$$\sum_{i \in D} \sum_{a \in A} CI_a^i * CP_a + \sum_{i \in D} E_i * ST_G^i + \sum_i T_{i \in D} * DL_i = TPC \tag{3.12}$$

3.6 Evaluation Results

To compare the performance of the above approaches, the total traffic power consumption of the cloud based IoT network for our proposed schemes is evaluated. The radio communication of the sensor nodes is Wi-Fi, based on 2.4 GHz frequency, and has an IEEE

802.11b standard. The values of the energy per bit (Ei) and the idle power ($IDLEi$) are real ones taken from different energy efficient IoT devices datasheets, namely: SPWF04SA, SPWF04SC datasheet [133], ESP32 datasheet [134], ESP8266EX datasheet [135], ZG2100M/ZG2101M Wi-Fi® Module data Sheet [136], CC3100 SimpleLink™ Wi-Fi® Network Processor, Internet-of-Things Solution for MCU Applications [137], CC3200MOD SimpleLink™ Wi-Fi® and the Internet-of-Things Module Solution, a Single-Chip Wireless MCU [138].

It is assumed that there is a smart city containing three smart buildings, and each has 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, as shown in Figure 3-2. The detailed evaluation parameters are summarised in table 3-4.

Table 3- 4: 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

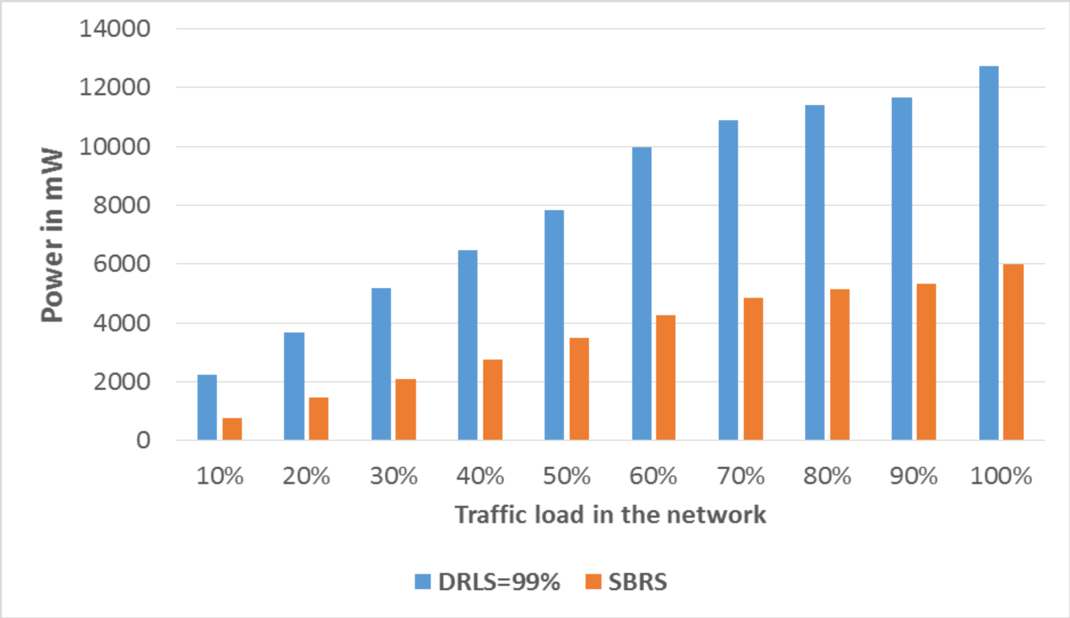


Figure 3-3: Total traffic power consumption in mW of a different number of devices when the link bit rate is 500 kbps for each node: a) energy efficient network optimisation with DRLS =99% and b) energy efficient network optimisation with SBRS.

The results in Figure 3-3 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 Figure 3-3, it is observed 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 minimise power.

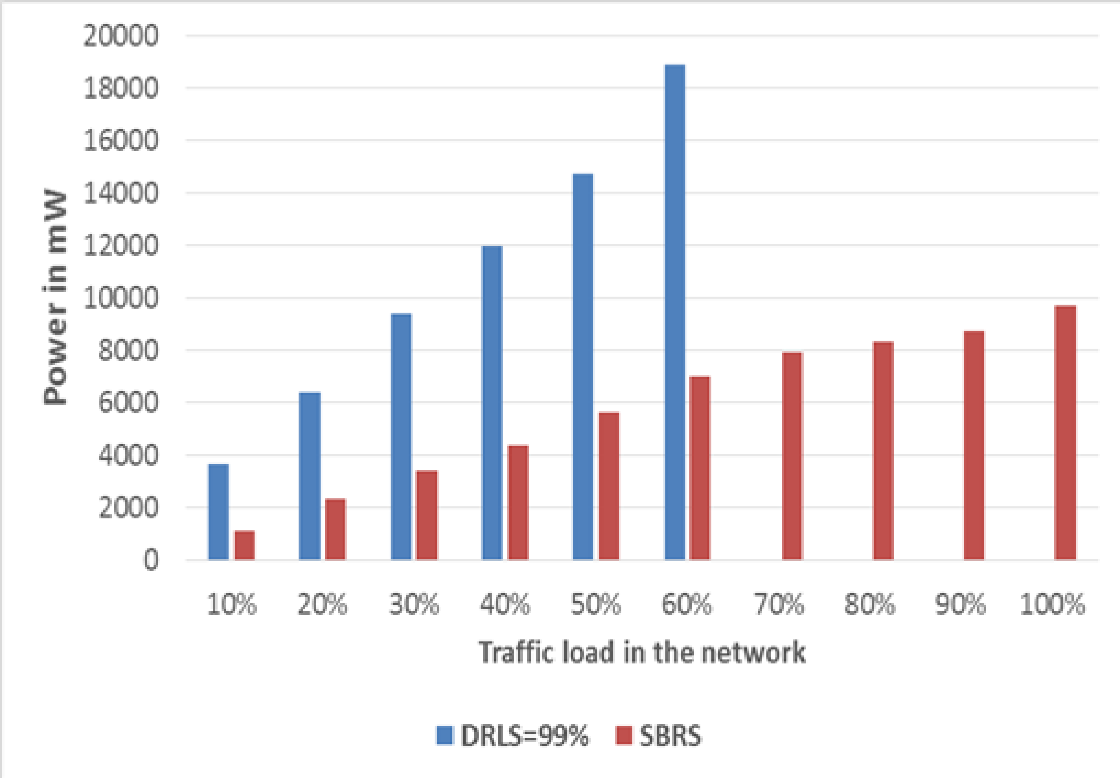


Figure 3-4: Total traffic power consumption in mW of a different number of devices when the link bit rate is 1000 kbps for each node: a) energy efficient network optimisation with DRLS =99% and b) energy efficient network optimisation with SBRS.

The results in Figure 3-4 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 the capacity limit. However, in SBRS, the network still works even when fully loaded because there is no overhead over links.

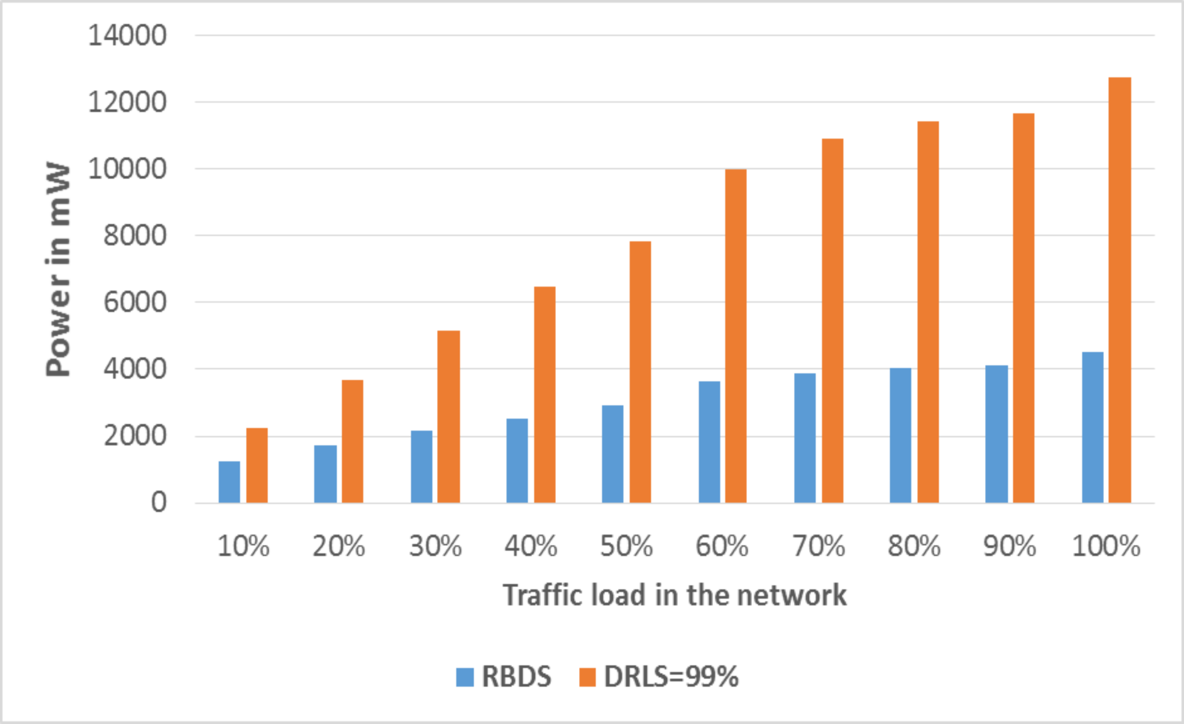


Figure 3-5: Total traffic power consumption of cloud based IoT network when the link bit rate is 500 kbps for each node: a) energy efficient network optimisation with DRLS =99%; b) energy efficient network optimisation with RBDS.

The total traffic power consumption of the cloud based IoT network in mW for DRLS and RBDS systems, versus a different number of IoT devices that generate 500 kbps of bit rate for each device is shown in Figure 3-5. 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.

Figure 3-6 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 Figure 3-6, it is observed that for the RBDS model, the network still works when fully loaded with a link bit rate of 1000 kbps, even when the

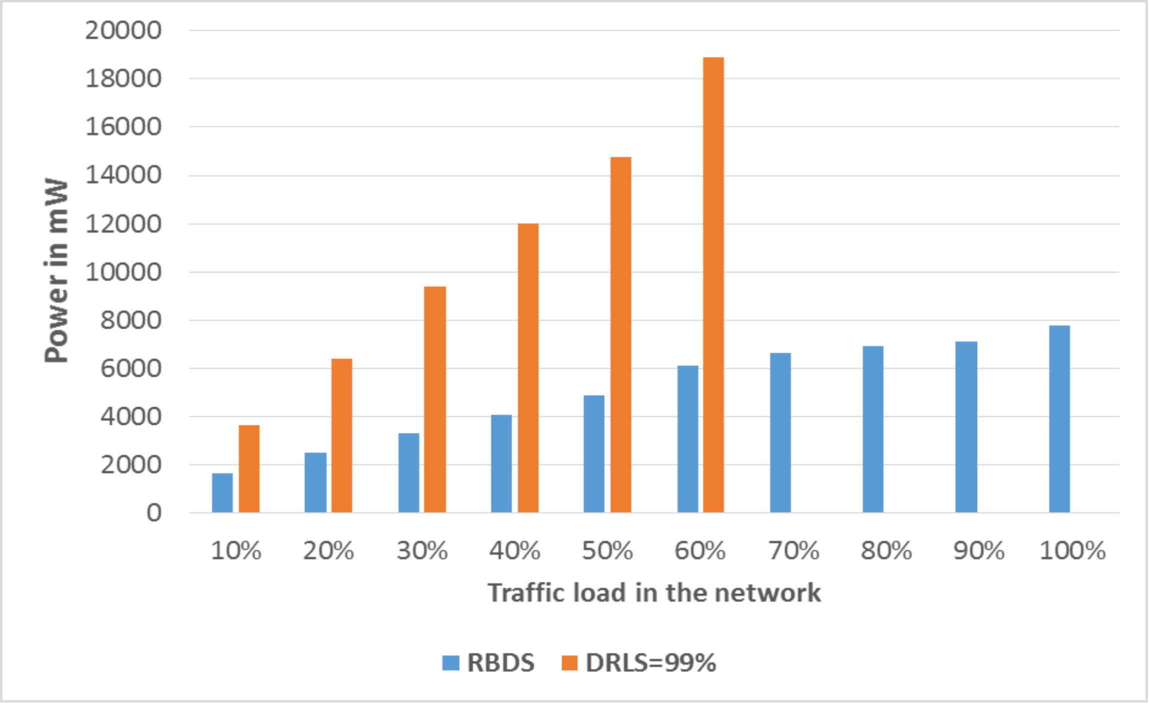


Figure 3-6: Total traffic power consumption of cloud based IoT network when the link bit rate is 1000 kbps for each node: a) energy efficient network optimisation with DRLS =99%; b) energy efficient network optimisation with RBDS.

link reliability is 99%, due to minimising the traffic using an S-LEC data compression scheme.

The evaluation results with respect to multi-channel usage to avoid link overhead and reduce interference are shown in Figure 3-7. 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 Figure 3-8 show the total traffic power consumption of the cloud based IoT network in mW for two scenarios of DRLS, first with a 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.

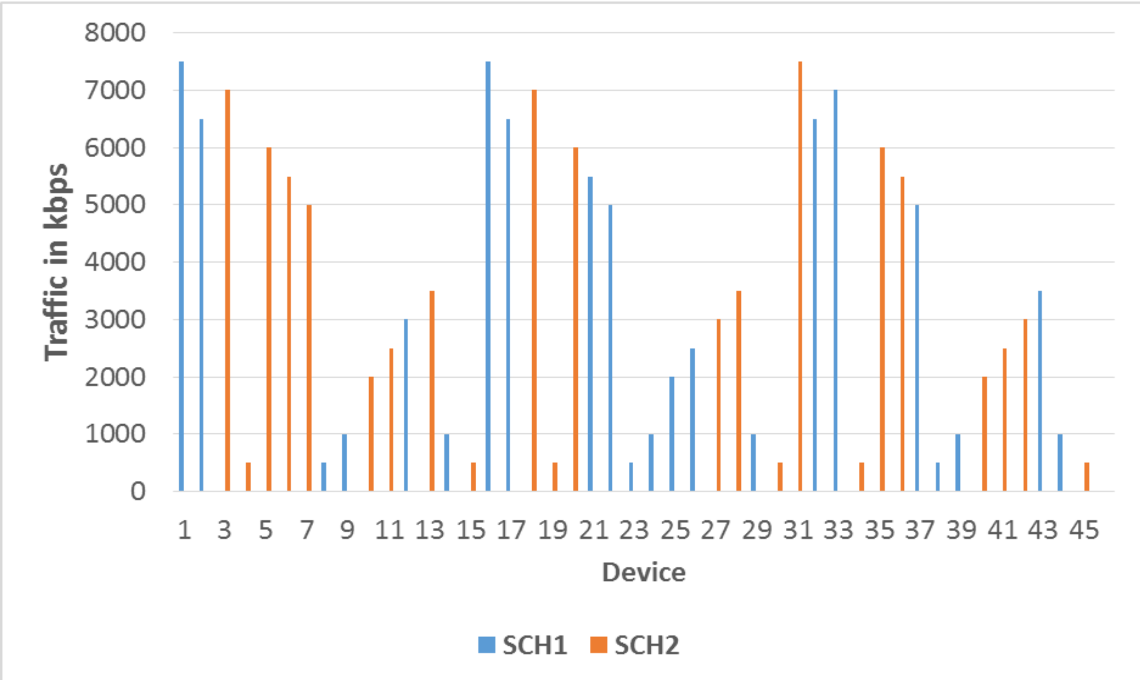


Figure 3-7: Interference avoidance by distribution of nodes on sub-channels.

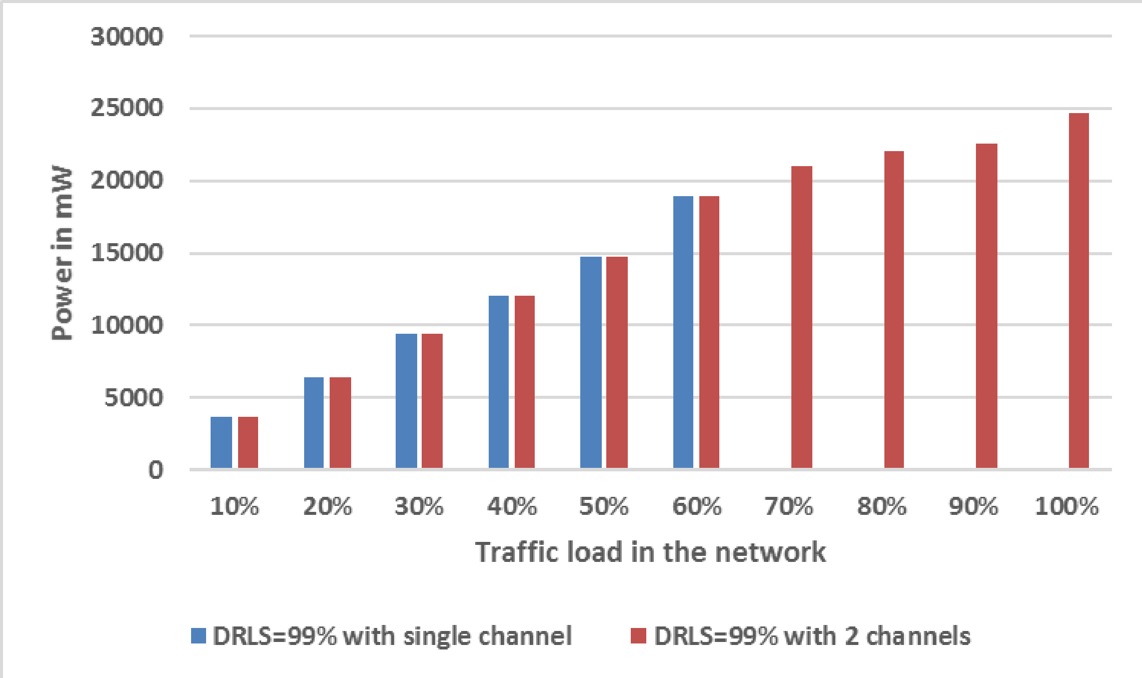


Figure 3-8: Total traffic power consumption in mW of a different number of IoT devices when the link bit rate is 1000 kbps for each node: a) energy efficient network optimisation for DRLS =99% with a single channel and b) energy efficient network optimisation for DRLS =99% with two channels.

Chapter 4

4 Energy Efficient Traffic in Cloud based IoT

In this chapter, an energy efficient cloud based IoT network model has been developed, through optimisation of the sensor selection, choosing the minimum number of hops and exploiting fading sub-channel gain to reduce traffic power and cancel interference. The optimisation model and results are conducted using the MILP. The model evaluates the results for two scenarios: First, energy efficient network optimisation by minimum hops and then, comparing the results with the second scenario of energy efficient network optimisation by minimum hops and sub-channel selection. From the results, it is concluded that the first scenario consumes more traffic power in IoT devices, while the second, minimises the traffic power of the network by an average of 27%.

4.1 Introduction

The pervasive connection of things will inevitably give rise to the generation of a massive amount of data, which will need to be processed, stored, and accessed. However, while IoT includes a large number of interconnected devices, these have limited power resources, processing and storage. Hence, efficient, secure and scalable computing and storage resourcing are necessary. Cloud computing has been recognised in recent times as a prototype for massive data storage and analyses in an efficient way. Integration of cloud computing and IoT can permit ubiquitous sensing services and forceful processing of sensed data.

In much research about cloud computing based IoT, the processing has been initiated from the IoT devices, such as sensors to the cloud, which represents the data centre. In contrast, the idea behind our research is taking the cloud operations that exploit IoT as information resources. That is, the cloud operations could be simplified into data collection from IoT devices. Where, in our model, the cloud should allocate the logical tasks, coming from the user's application, into a specific IoT device that match the logical task requirements like location and function. Our model provides an optimal energy efficient path between IoT devices to the cloud by hop routes minimisation and fading sub-channel gain utilisation. Generally, the most power consumed is in the radio transmission unit when compared to the other IoT device units (i.e. microcontroller and memory) [146].

Each IoT device plays a dual role as a data router and a sender. Therefore, the smart devices regularly suffer from interference generated by surrounding devices. It also causes more congestion in the shared frequency of 2.4 GHz, which may cause bandwidth limitation [46]. That leads to loss of connections and thus resulting in packet drops leading to degraded communication link quality. Interference significantly reducing the energy transmission efficiency [139], therefore, mitigating the interference, would dramatically improve the energy efficiency of the whole network. By using multichannel communication in wireless networks, the effects of interference can be reduced to enable the network to operate reliably.

Assuming, software defined networking (SDN) in the cloud, SDN architecture aims to introduce a centralised control server (controller) to permit easy, flexible network programming. SDN exploits the capability of separating the data plane from the control plane in switches and routers (hardware), where the control plane can send instructions to the data plane of the hardware [140, 141].

In this chapter, the routing of cloud based IoT is suggested for use in IoT networks as a promising technology for minimising the total traffic power consumption through the following:

- Developing a MILP model to virtualize cloud based IoT network.
- Selecting the routes that have the minimum number of hops between IoT devices and the cloud.
- Minimising the number of power ON devices.
- Load balance through the gateways to avoid traffic congestion to the cloud in the IoT network.

- Selecting energy efficient sub-channels by exploiting the fading sub-channel gain;
- Utilising time slots of the energy efficient sub-channels;
- Reducing interference through sub-channel selection.

In this chapter, two optimisation scenarios are implemented, in the first of which, the model minimises the traffic power consumption through hops minimisation, i.e. reducing the number of repeaters in the network. In the second scenario, the model minimises the traffic power consumption through optimising the fading sub-channel gain selection and hops minimisation. The attainable performance and comparison of the two scenarios are analysed and discussed in detail.

4.2 Cloud based IoT System

In this work, it is assumed that there is a real-world scenario, such as smart buildings in a smart city with multiple applications [126], [127], which are performing in the cloud and requiring data collection such as sensing a temperature of the surrounding environment. The data is collected by sensors in IoT devices, with the devices having specific characteristics and being connected to the cloud through gateways. Physically, in the devices layer, there are a vast number of IoT devices, which are distributed arbitrarily according to their abilities, such as sensing and location. Moreover, each IoT device is sending its collected data to the cloud continually, which has the computation function of analysing these data and using them according to their applications.

In other words, cloud computing provides a platform as a service (PaaS), through which the users can run, manage, and develop their applications. These applications depend on the information that needs to be collected from IoT devices, for example, an application demand for real time information such as temperature or humidity in a specified area in the city, and the application layer will pass this demand to the cloud. The cloud needs to evaluate and process this, subsequently sending the results to the application layer. 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.

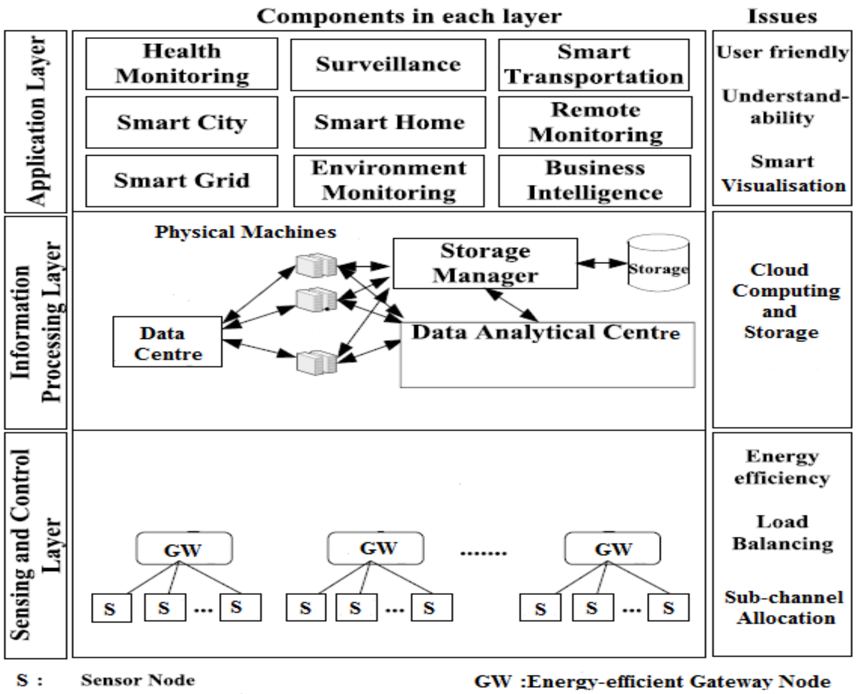


Figure 4-1: The proposed architecture of cloud based IoT.

The proposed architecture in our model is presented in Figure 4-1, and it consists of three layers [75]:

1- Sensing and control layer - It contains the low-powered sensors, actuators and gateways. (It gathers the data and sends them for analysis).

2- Information processing layer - The data collected via the sensors are in unprocessed form and huge volumes, to extract interpretable information from these data, they need to be stored, processed, and analysed. These tasks are accomplished by this layer, which uses the cloud computing platform to provide storage and analytical data tools; it comprises a data analytics centre, storage media, and different physical machines.

3- Application layer - It is responsible for the visualisation of the processed data and producing them in an innovative and simply readable form to the users. It offers services to the end users by providing an interface for applications such as health monitoring, smart transportation or environment monitoring.

Data transmission from the IoT network to the cloud is done through a gateway, which is because the physical world (IoT network) is connected to the cloud and both of them have different protocols for communication.

4.3 Network Optimisation Model of Cloud based IoT

Our mathematical model is developed by using MILP, which is mathematical programming that can achieve optimisation of a function of many variables subject to constraints. As explained above, it is assumed a cloud based IoT system. The IoT devices are distributed in one physical grid; in this case, smart buildings, which consists of 60 IoT devices connected by a physical network distributed across four buildings, as shown in Figure 4-2.

It is supposed that these smart buildings (B) each have three floors (F), each with 5 IoT devices, which means that each building has 15 IoT devices. The central node in the second floor of each building serves as a gateway to collect data to send to or receive from the cloud, as explained in Figure 4-3. Each IoT device is linked to their neighbours through a physical plan. The floors are connected through the central nodes of 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.

Each IoT device can process, store, and function, additionally, it has two of the following functions: alarm, security, climate and/or entertainment. The topology of IoT network that has been used here is a star, as shown in Figure 4-3, in which each sensor node communicates with its neighbour and can relay messages from that neighbour through the network [130].

The model considers that each IoT device has connected to variant sensors (S) with particular specifications, which are the functionality of each node and location. The MILP model will optimise the selection of the path between the IoT devices and the cloud in an energy efficient matter in terms of minimising total power consumption and providing

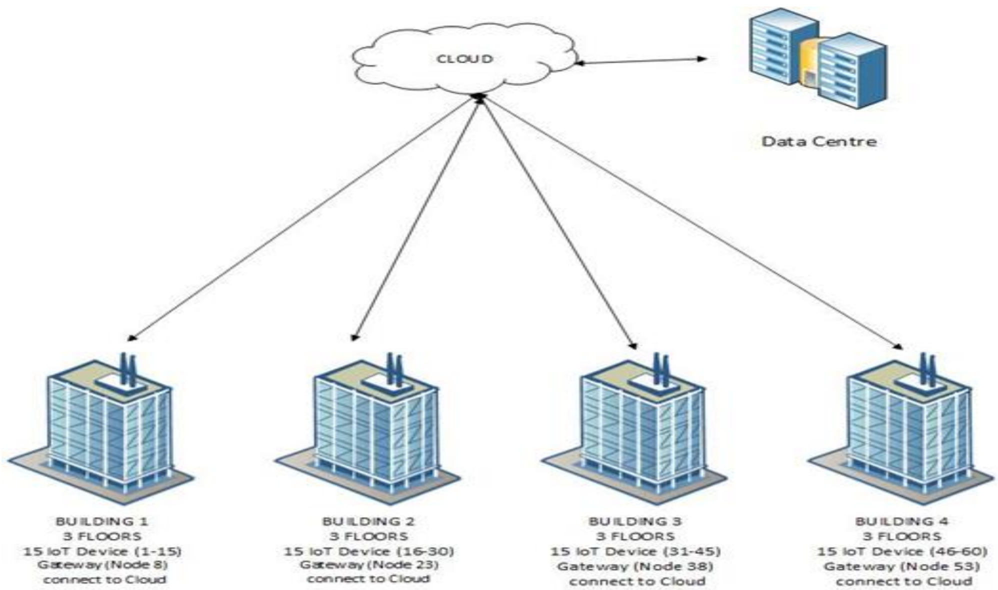


Figure 4-2: Physical network of a smart city.

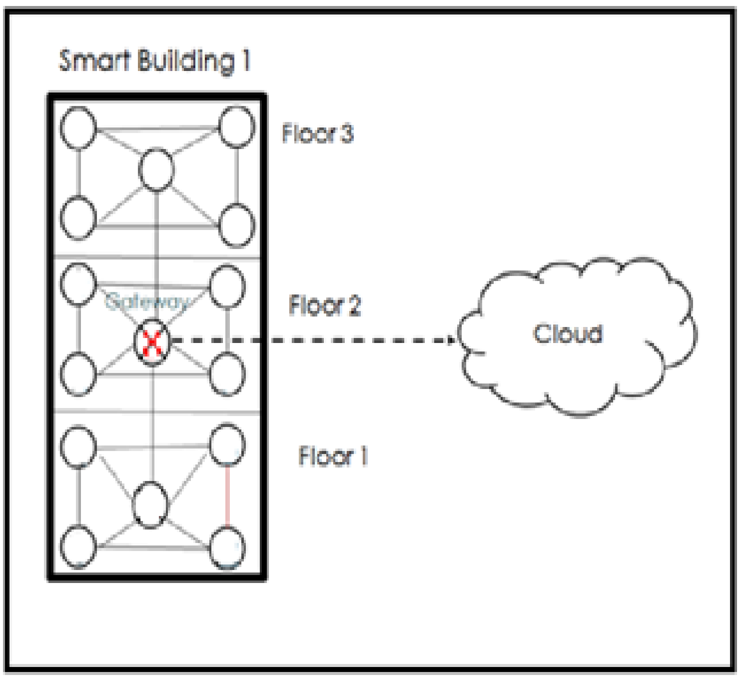


Figure 4-3: Topology of one of the smart buildings in the proposed IoT network of a smart city.

network optimisation. That means the model selects the optimum IoT device and optimum fading sub-channel gain for each logical node, based on the ability of the IoT device, with minimum traffic power consumption and an energy efficient network path.

Table 4- 1: List of the variables used in the MILP model

Variable	Description
LK_G^d	Variable of end to end Link
$R_{j\ i\ c\ ts}^{D\ G}$	Variable indicator for full path route in physical plan between device and cloud through the repeaters nodes (i, j) where j is a neighbour of i, IoT devices through (c) sub-channel (sch), and time slot (ts).
$\mathrm{TF}_{c\ \ ts}^{\mathrm{d}}$	Variable indicator for the ON IoT device and its corresponding sub-channel in the 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.

Table 4- 2: List of the parameters used in the MILP model

Parameter	Description
ts	Parameter of the number of time slots.
M	Integer number.
sch	Set of sub-channels.
$NB[i]$	Parameter of the neighbours 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.

Table 4- 3: List of the sets used in the MILP model

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

4.4 Objectives of the Proposed Model

1- Minimising the Number of Hops: The routing concept in this chapter is based on the flow conservation constraint for the traffic flows in the physical network by Tucker [131].

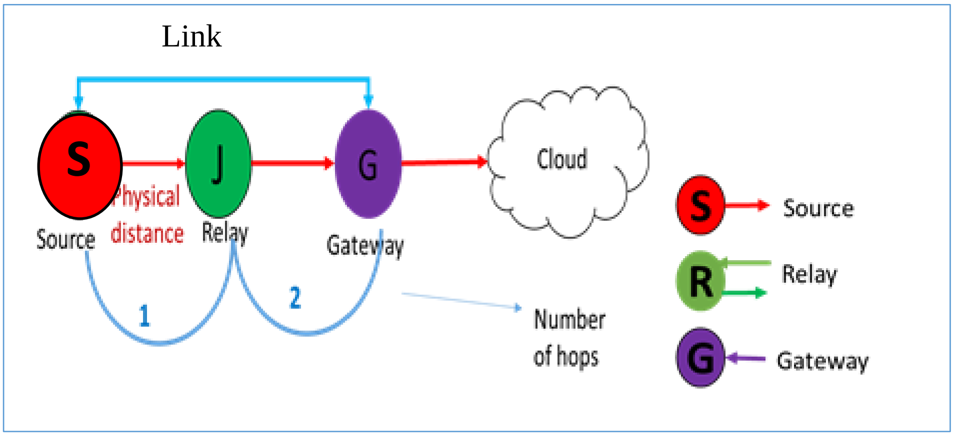


Figure 4-4: Routing between an IoT device and the cloud in the physical network.

A parameter LK_G^d is created, which indicates the traffic (link) between the IoT device (d) and the cloud (G).

$$LK_G^d = \begin{cases} 1 & \text{If there is link between the IoT Device and the Cloud} \\ 0 & \text{Else} \end{cases} \quad (4.1)$$

A binary variable $R_{i\ j\ c\ ts}^{d\ \ G}$ is formed, which represents the route between the IoT device (d) and the cloud.

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

$$\{\sum_{j\in D, i\neq j} \sum_{c\in sch} \sum_{ts\in T} R_{i\ j\ c\ ts}^{d\ G} - \sum_{j\in D, i\neq j} \sum_{c\in sch} \sum_{ts\in T} R_{j\ i\ c\ ts}^{d\ G}\} = LK_G^d \quad (4.2)$$

$$\{\sum_{j\in D, i\neq j} \sum_{c\in sch} \sum_{ts\in T} R_{i\ j\ c\ ts}^{d\ G} - \sum_{j\in D, i\neq j} \sum_{c\in sch} \sum_{ts\in T} R_{j\ i\ c\ ts}^{d\ G}\} = 0 \quad (4.3)$$

$$\{\sum_{j\in D, i\neq j} \sum_{c\in sch} \sum_{ts\in T} R_{i\ j\ c\ ts}^{d\ G} - \sum_{j\in D, i\neq j} \sum_{c\in sch} \sum_{ts\in T} R_{j\ i\ c\ ts}^{d\ G}\} = -LK_G^d \quad (4.4)$$

Flow conservation constraint has three possibilities, as shown in Figure 4-4 and equations (4.2-4.4). 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, then it is a destination.

The model optimises the network paths by selecting the route that has the minimum number of hops (H), and the objective function is to minimise H.

Objective: Minimise

$$\sum_{\substack{d \in D, \\ d \neq G}} \sum_{i \in D} \sum_{j \in D, i \neq j} \sum_{c \in sch} \sum_{ts \in T} R_{i\ j\ c\ \ ts}^{d\ G} = H \tag{4.5}$$

where

H: Variable

D is the set of IoT devices, *T* is the set of time slots, *sch* is the set of sub-channels.

$R_{i\ j\ c\ ts}^{d\ \ G}$ 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 neighbour of *i*, through *c* sub-channel, and time slot ts.

The lists of variables, parameters and sets defined in the MILP model are briefly highlighted in tables (4-1 – 4-3).

2- Interference Cancellation: To cancel the interference, adopted three constraints have been adopted:

First, the traffic path is only one between the device and the cloud.

$$\sum_{j \in D, i \neq j} \sum_{c \in sch} \sum_{ts \in T} R_{i\ j\ c\ ts}^{d\ G} \leq 1 \tag{4.6}$$

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

Second, each IoT device must use only one sub-channel in each transmission or else 0 sub-channels to avoid transmission repetition.

$$\sum_{ts \in T} \sum_{c \in sch} DB_b^d \, DF_f^d \, TF_{c \quad ts}^d \leq 1 \tag{4.7}$$

$\forall$ d $\in$ D, $\forall$ b $\in$B, $\forall$ f $\in$ F.

where

DB_b^d is the IoT device's building address, DF_f^d is its floor address and TF_c^d is as an indicator for the power ON device and the corresponding selected sub-channel and time slot.

The third restriction is that for each floor there is a specific number of sub-channels (sch) and the number of devices that use a particular sub-channel is equal to the number of time slots of that sub-channel or less. That is to avoid interference.

$$\sum_{ts \in T} \sum_{d \in D} DB_b^d \, DF_f^d \, TF_{c \quad ts}^d \leq \sum_{ts \in T} ts \tag{4.8}$$

$\forall$ b $\in$B, $\forall$ f $\in$ F, $\forall$ c$\in$ sch.

3- Maximising fading channel gain: The following restrictions evaluate the transmitted (traffic) power in dBm for each device. The model goal is to minimise $TFP\ (d)$, thus by selecting the highest fading channel gain.

Objective: Minimise

$$-74 * ON_d - \sum_{c \in sch} \sum_{ts \in T} TF_{c\ \ ts}^{d} * FG_c^d + ON_d * Noise_d = TFP\ (d) \qquad (4.9)$$

$\forall d \in D$

where,

Equation (4.9) derived from the following fading channel equation:

$$Y = H\,X + N \qquad (4.10)$$

where X: denote the transmitted signal, Y: denote received signal, H: denote the fading channel gain, N: denote a zero-mean Gaussian random variable with variance σ^2[142]. Equation (4.10) which in dBm refers to:

$$Y = H + X + (-N)$$

$$X = Y - H + N \qquad (4.11)$$

Equation (4.11) corresponds to equation (4.9) where, (FG_c^d) is the fading sub-channel gain factor for the c sub-channel for device d, $(Noise_d)$ is the noise for each IoT device and (ON_d) refers to the transmitting devices. The value -74 is the average receiver sensitivity, as explained in table 4-4. In such method, a minimum transmitted power level is defined to control the interference so that the QoS of IoT applications users can be guaranteed due to the low interference strength from IoT devices transmitters.

The following restriction evaluates the total transmitted power.

Objective: Minimise

$$\sum_{d \in D} TFP(d) = TTP \qquad (4.12)$$

Finally, the model optimises overall network traffic power consumption, through minimising total traffic-power and the minimisation of hops.

Table 4- 4: CC3200 SIMPLELINK WI-FI Parameters

Parameter	Value
TX Power	14.5 dBm
RX Power	–74.0 dBm
V_{BAT}	2.1 to 3.6 V
RX Traffic	59 mA
TX Traffic	229 mA

4.5 Performance Evaluation

In order to evaluate the performance of the model, it has been run it for two scenarios of optimisation. The first involves reducing the number of hops only, whilst for the second, the hops are reduced, and optimal selecting of the highest fading sub-channel gain is deployed. The model has been run for up to request multi devices simultaneously. The power parameters of an IoT device is as mentioned on the datasheet of CC3200 SimpleLink Wi-Fi [143]. Furthermore, CC3200 supports most Arduino compatible shields [144]. Table 4-4 displays the features of CC3200 which have 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 [138] and are summarised in table 4-5. A Rayleigh fading channel is assumed since Rayleigh distribution best describes the envelope of a fading signal [142]. Regarding the number of sub-channels, more than two sub-channels can be supposed in the model, for example, we can add four sub-channels, however, in this case, the assumption of IEEE802.11 should be removed, and this will not affect the overall results.

Table 4- 5: Model Parameters

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

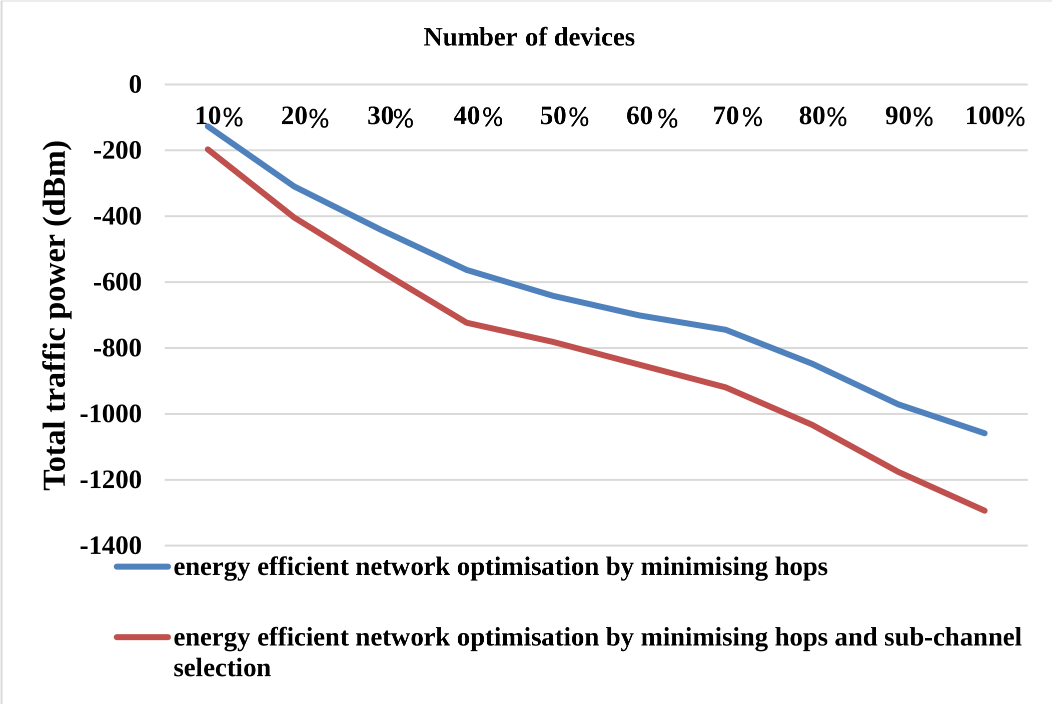


Figure 4-5: Total traffic power in dBm of different numbers of devices for a) energy efficient network optimisation by minimising hops; and b) energy efficient network optimisation by minimising hops and sub-channel selection.

Figure 4-5 displays the total traffic power in dBm of our model versus the variant percentage of the number of IoT devices that generate traffic. In Figure 4-5 (a), the model minimises the number of hops by selecting the shortest path between the device and the cloud. Besides, the model minimises power consumption by link utilisation.

Also, Figure 4-5 (b), displays the second scenario of energy efficient network optimisation for the same number of devices and physical network, with the objective of additional traffic power minimisation. By minimising the number of hops of the routes and the traffic power by selecting the highest fading sub-channel gain, and by utilising the time slots of the energy efficient sub-channel according to (4.11), this can be achieved. Figure 4-6 reveals that the average power saving in the second scenario of energy efficient network optimisation is about 27.44%. This saving results from the optimal selection of high gain sub-channels, to which the random sub-channel selection and utilisation of the time slots of these sub-channels 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 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 traffic power in the device circuit, in mW and radiated power in the air in dBm. Table 4-6 displays the mapping approach followed in this work as below:

Where these values are considered from reference [24] and table 4-4. Maximum transmitted power in mW (2.9 volt* 229 mA= 680 mW) corresponds to the maximum transmitted power in dBm (14 dBm). While the minimum transmitted power in mW (3 volt* 59 mA= 180 mW) corresponds to the minimum transmitted power in dBm (-40 dBm).

Table 4- 6: Mapping Approach

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

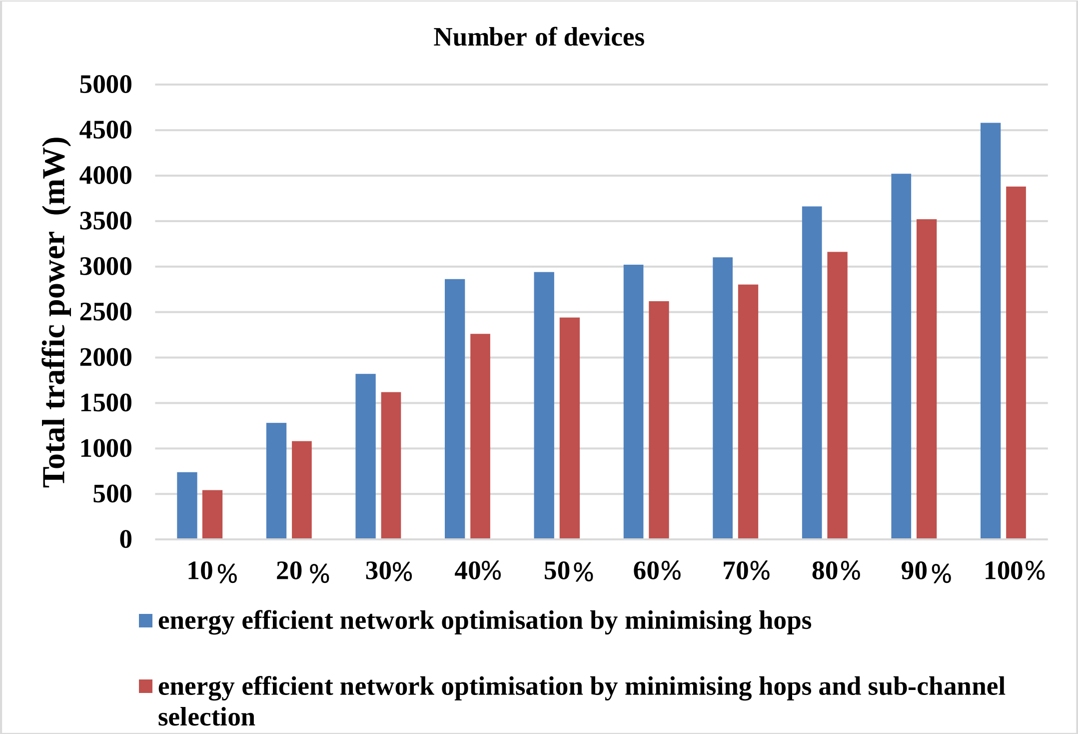


Figure 4-6: Total traffic power in mW of different number of devices for a) energy efficient network optimisation by minimising hops and b) energy efficient network optimisation by minimising hops and sub-channel selection.

Figure 4-6 displays the model results of total traffic power in mW for energy efficient network optimisation by minimising hops and compares this with the total traffic power of energy efficient network optimisation by minimising hops and sub-channel selection for the same number of devices. The total traffic power is represented in (4.12). From the results, it is concluded that energy efficient network optimisation just by minimising hops consumes more traffic power in IoT devices than when sub-channel selection is included for the same number of devices. That is, optimal high gain sub-channel 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 sub-channel 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 non-optimal sub-channel as the IoT device's increased. Furthermore, IoT device's distribution is non-homogenous (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.

Chapter 5

5 Energy Efficient Data Compression in Cloud based IoT

This work is complementary to **chapter 4**, that aims at achieving energy efficiency through minimising transmission power consumption of a cloud based IoT network through circuit power consumption minimisation.

In this chapter, an adaptive data compression scheme (ADCS) is proposed for efficiently controlling the IoT device compression rate and power consumption in the cloud based IoT network. The ADCS consists of two data compression schemes, the sensor Lempel–Ziv–Welch (S-LZW) scheme and the sequential lossless entropy compression (S-LEC) scheme. In Auto state, the ADCS can select the appropriate energy efficient data compression scheme for each IoT device, while taking into consideration the IoT device's processing capability, the available energy in each IoT device battery (10% of total battery level) and the amount of compression power. Our proposed scheme has been developed using mixed integer linear programming (MILP). The result verifies that the proposed ADCS scheme saves power by an average of 40% compared to the non-compression scheme (NCS) due to reducing the traffic load and number of hops in the network, which leads to an ability to handle higher traffic demands and increasing the lifetime (tasks cycles) of IoT devices by 50% compared to NCS systems.

5.1 Introduction

In recent years, cloud computing has attained huge popularity due to its vast storage and processing capabilities. However, IoT devices have limited energy and processing capabilities. Hence, IoT networks are integrated with the cloud environment to help in the storage and processing of data [145]. Energy efficiency is a critical aspect in IoT design and deployment, as IoT devices are usually battery-powered, and it is often difficult, expensive or even dangerous to replace the batteries in many real physical environments. Generally, more power is consumed in radio transmission and reception when compared to that of other node units (e.g. the microcontroller and memory) [146]. Effective data compression is imperative for reducing the power consumption of IoT devices.

Some data compression schemes are dedicated to IoT networks; in this paper, a sensor Lempel–Ziv–Welch (S-LZW), [106], and a sequential lossless entropy compression (S-LEC) [146] are used. These are lossless, energy efficient approaches with high compression ratios to minimise transmitted power. A smart building contains different electrical and electronic devices that can be monitored and controlled by smartphones or a PC, making modern buildings smart is a significant step towards a smart city that will enable future automation and optimisation. Smart buildings also improve energy management by minimising energy loss through the intelligent control of the high energy requirements of building devices, where smart building application incorporates IoT into their infrastructure.

Generally, IoT devices have limited hardware resources, such as energy, storage and processing, which restrict the lifetime of a network. Hence, there is a need for efficient sensor network's data compression schemes that do not consume high energy in processing or communication to decrease energy demands. The notion of data compression has been around since the early days of computers [147], [148], [149] with many techniques for wireless sensor networks having been proposed recently to address the different restrictions and limitations of WSN [146], [150], [117], [115], [109]. The goal of data compression is to minimise the amount of data to be transmitted over wireless channels. The format of the compressed data requires few bits, which leads to a minimisation in the required inter-node communication, which considerably lessens the energy demand, thus extending the lifetime of an IoT device [151]. There are two components of a data compression task, as shown in Figure 5.1. First, there is an encoding algorithm that converts a message into a compressed representation, which has the same data with as low length as possible. Secondly, a decoding algorithm reconverts the compressed representation into the original or nearly original message [152], [153]. Data compression techniques can be classified into two main types: lossy and lossless.

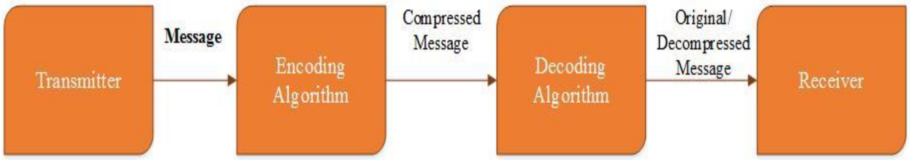


Figure 5-1: Representation of data compression components.

While some of the problems of the IoT have been already addressed (i.e. energy efficiency, reliability and interference cancellation) in our previous work [145], [132]. The MILP model has been developed to reduce the total traffic power of cloud based IoT network through:

- Constrains battery level to be within 10% of total battery level to increase the lifetime and the tasks cycles for each IoT device.

- Optimising the selection of IoT devices with minimum energy per bit and idle power.

The ADCS means it can use more than one data compression scheme and switch between them. In our work, used two schemes are used: S-LZW and S-LEC. The energy consumption of ADCS is discussed and compared to the non-compression scheme (NCS) to show its effectiveness. Also, the ADCS in Auto state is proposed, which calculates how much power saving each data compression scheme would produce and selects the most energy efficient one (in our work, the S-LEC).

The contributions of this chapter are summarised as follows:

- Design of a cloud based IoT network using a MILP model.
- Reducing the network power consumption through ADCS.

- Maximising network lifetime and number of tasks cycles through battery level constrain.
- Handling more traffic demands through data compression schemes.
- Optimise the selection of IoT devices that have the minimum energy per bit and idle power.
- Load balance through the gateways to avoid traffic congestion to the cloud in the IoT network.
- Minimising the number of power ON devices.

5.2 Data Compression Techniques

Recent advances in lossless data compression algorithms include S-LZW and S-LEC, which are explained below.

LZW basics: LZW is a lossless, dictionary lookup-based algorithm that does not build its dictionary in advance, but rather, dynamically creates it based on the raw input stream [154]. It is a good fit for WSN because the dictionary structure permits it to generate varied dictionaries according to the varied compressed contents and take advantage of repetition in the data. LZW replaces strings of characters with single codes in the dictionary. The algorithm sequentially reads in characters and finds the longest string ω that can be recognised by the dictionary. Then, it encodes ω using the corresponding codeword in the dictionary and adds string ω +k to it, where k is the character following string ω. This process continues until all characters are encoded [116].

S-LZW algorithm: S-LZW is a dictionary-based lossless compression algorithm used in resource-constrained WSN, because of its high compression ratio and lightweight. It is a modified version of the well-known LZW compression algorithm. It involves decreasing the weight of that algorithm, which has been used commonly in desktop PC environments [155, 156]. To adapt LZW into a sensor node, it needs to balance three main inter-related points: the size of the dictionary, the size of the data that need to be compressed, and the followed protocol when the dictionary fills. Most importantly, the memory restrictions require that LZW retains a dictionary size as small as possible. To decode a dictionary entry, however, all previous entries in the block must have received by the decoder. Unfortunately, the source never receives 100% of the sensor node data. To address this, the S-LZW algorithm separates the data stream into small, independent blocks, so only those following the lost packet are affected [106, 155].

LEC algorithm: LEC is a simple lossless entropy compression algorithm, which can be performed in a few lines of code and involves very low computational power, whilst compressing data on the fly [157]. Besides, the used dictionary is very small, with its size being determined by the resolution of the analogue-to-digital converter. It is particularly suitable to be used on available commercial tiny sensors due to its low complexity and the small size memory needed for its execution. LEC is based on predictive coding [150], in which a predictor and an encoder are used. For a new data entry xi in a series, $\hat{xi}$ is produced by a specified predictor, and the remainder $ri{=}xi{-}\hat{xi}$ is calculated. This remainder ri is coded and then, sent to the receiving node. The differential predictor adopted in LEC is simple and popular, that is $\hat{xi}{=}xi{-}1$.

S-LEC algorithm: LEC has a general and non-adaptive predictor that cannot efficiently exploit temporal correlations for different WSN data streams for diverse WSN applications. To address this, a Sequential Lossless Entropy Compression (S-LEC), is proposed, which is a devised algorithm that extends the LEC to address its frailty of the shortage of robustness. S-LEC is capable of achieving highly robust compression performance for different sensor data streams; simultaneously, it enables energy-efficient employment and execution on resource-constrained WSN nodes in a relatively simple manner. The performance of a compression algorithm is usually evaluated by the compression ratio defined as follows [146]:

$$CR = (x^\wedge/x) \tag{5.1}$$

where, $x^\wedge$ and x are the numbers of bits used to represent the transmitted (compressed) and the original data, respectively. Table 5-1 shows the compression ratio and compression energy of both algorithms used in the model. S-LEC has a higher compression ratio and power consumption when compared to S-LZW.

Table 5- 1: A comparison of compression algorithms

Data compression algorithms	**Compression Rate**	**Compression power mW/byte**
S-LZW	0.5101	0.00165
S-LEC	0.2793	2.897

5.3 Proposed Model of the Adaptive Data Compression System

For this work, it is supposed there is a real-world scenario of smart buildings in a smart city with multiple user applications where the user application is performing in the cloud and requesting data collection. The data are gathered by sensors in IoT devices which are connected to the cloud via the gateways. Our proposed architecture of cloud based IoT is built by deploying three layers: 1- Sensing and control layer, with the data being gathered in this layer and sent to the cloud for analysis. 2- Information processing layer, which comprises a data analytics centre and storage media to process and analyse the unprocessed data. 3- Application layer, offering services to the end users by providing an interface for applications such as a smart building. A cloud based IoT system has been proposed where the IoT devices are split into one physical grid in smart buildings. Specifically, the grid comprises a number of 60 IoT devices connected through a physical network separated across four building, as shown in Figure 5-2.

Each smart building has four floors, and each building includes 15 IoT devices. The nodes on the first and second floor of each building serve as gateways to collect data to send to the cloud. Each IoT device is linked to its neighbours through a physical plan, with a star topology being proposed in this work, as shown in Figure 5-3. Each IoT device has processing, storage, and functionality capabilities (climate functions). In the model, it has been considered that each IoT device is connected to variant sensors with particular specifications, i.e. functionality and location.

Figure 5-2: Illustration of the proposed IoT physical network of a smart city.

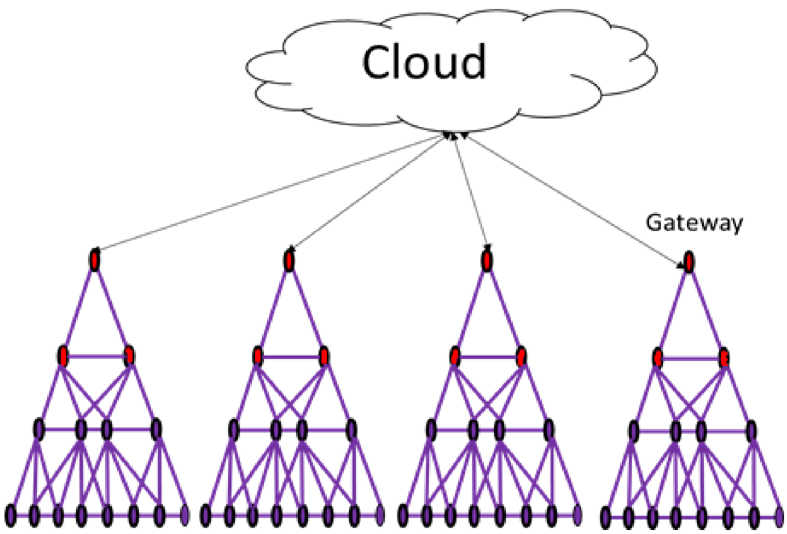


Figure 5-3: Topology of one of the smart buildings in the proposed IoT network of a smart city.

Table 5- 2: List of the sets used in the MILP model

Set	Description
D	Set of IoT devices.
A	Set of data compression algorithms.

Table 5- 3: List of the parameters used in the MILP model

Parameters	Description
CP_a	Parameter indicates the IoT device with its corresponding compression algorithm c.
E_i	Parameter indicates energy per bit for each IoT device in mW/kbps.
DL_i	Parameter indicates the idle power of each IoT device in mW.
CR_a	Parameter indicates the compression ratio of the compression algorithm.
BT_G^i	Parameter indicates data traffic between an IoT node and the cloud before compression.
B_i	The battery energy in joules of the IoT device.
P_i	The average power in joule required for transmission in the IoT device.

Table 5- 4: List of the variables used in the MILP model

Variables	Descriptions
CI_a^i	Variable indicates the IoT device with its corresponding compression algorithm.
NT_G^i	Variable indicates IoT device data traffic after compression.
T_i	Variable indicates the power ON IoT devices.

5.4 Objectives of the Proposed Model

1. Minimising Power Consumption

Mathematically, our proposed model is as follows:

The following constraint state the data traffic between the sensor node (i) and the cloud (G) after compression:

$$\sum_{a \in A} BT_G^i * CR_a * CI_a^i = NT_G^i \quad (5.2)$$

$\forall \ \mathrm{i} \in D$

where,

D is the set of IoT devices, A is the set of data compression algorithms, while T_G^i is a parameter representing the data traffic between the IoT device and cloud before compression. CR_a is the compression ratio of the specific data compression algorithm a, with CI_a^i being a variable pertaining to the IoT device and its corresponding compression algorithm. Finally, NT_G^i is a variable representing the data traffic after compression.

It has been proposed that the value of the IoT device bit rate should not exceed 10 Mbps. The key notation used in the optimisation model has been explained, which all are listed in tables (5-2 – 5-4).

The following restriction evaluates the total traffic power in the network, and the objective function is to minimise TP.

Objective: Minimise

$$\sum_{i\in D} CI_a^i * CP_a + \sum_{i\in D} E_i * NT_G^i + \sum_i T_{i\in D} * DL_i = TP \tag{5.3}$$

where,

CP_a represents the power consumed for compressing the data using the compression algorithm a. Also, E_i is the energy per bit for each IoT device in mW/kbps. The power ON device is indicated by T_i, the idle power in mW of each IoT device is indicated by DL_i whilst the values of the energy per bit (E_i) and the idle power (DL_i) are real ones taken from different IoT device datasheets, namely: SPWF04SA, SPWF04SC datasheet [133], ESP32 datasheet [134], ESP8266EX datasheet [135], ZG2100M/ZG2101M Wi-Fi® Module data Sheet [136], CC3100 SimpleLink™ Wi-Fi® Network Processor, Internet-of-Things Solution for MCU Applications [137], CC3200MOD SimpleLink™ Wi-Fi® and the Internet-of-Things Module Solution, a Single-Chip Wireless MCU [138].

2. Maximising Network Lifetime

It should be noted that providing energy efficiency in an IoT network does not guarantee that the battery life of a device will be long. Hence, it is important to consider the energy level of each IoT device battery before transmission and/or the data compression process. The following constraint ensures that the residual energy in the IoT device battery will be at least 10% of the battery level.

$$B_i - E_i * NT_G^i - T_i * DL_i - \sum_i CI_a^i * CP_a \geq 0.1 * B_i \tag{5.4}$$

where, B_i is the battery energy in joules of the IoT device, E_i is the energy per bit in joules and DL_i is the idle power of each IoT device in joules, whilst the battery level is from 100 – 600 joules [158], [159], [160]. Thereby, this constraint diminishing the threat of node failure and hence, extending the network lifetime. Furthermore, this battery level constraint increases the number of sub-operations of the IoT device. The following constraint evaluates the number of sub-operations of each IoT device:

$$\frac{B_i}{P_i} = N_i \tag{5.5}$$

where, P_i is the average power in joule required for transmission in the IoT device. The sub-operations are the number of the tasks of the node during its lifetime before it drops out.

5.5 Evaluation Results

In this section, the numeric results from the MILP formulation are presented to answer the following questions: (1) How does the ADCS system affect network in terms of energy efficiency? (2) What is the influence of the ADCS system on the IoT network when the data traffic increases? (3) What is the number of hops in the network, in ADCS and NCS systems? (4) How long is a node's lifetime in the network? To answer these questions, the model has been run for different scenarios of optimisation as follows: The first, has involved the non-compression NCS, whilst for ADCS, it includes (S-LEC, S-LZW) compression algorithms and the (Auto) scheme, which optimally selects the most energy efficient data compression algorithm.

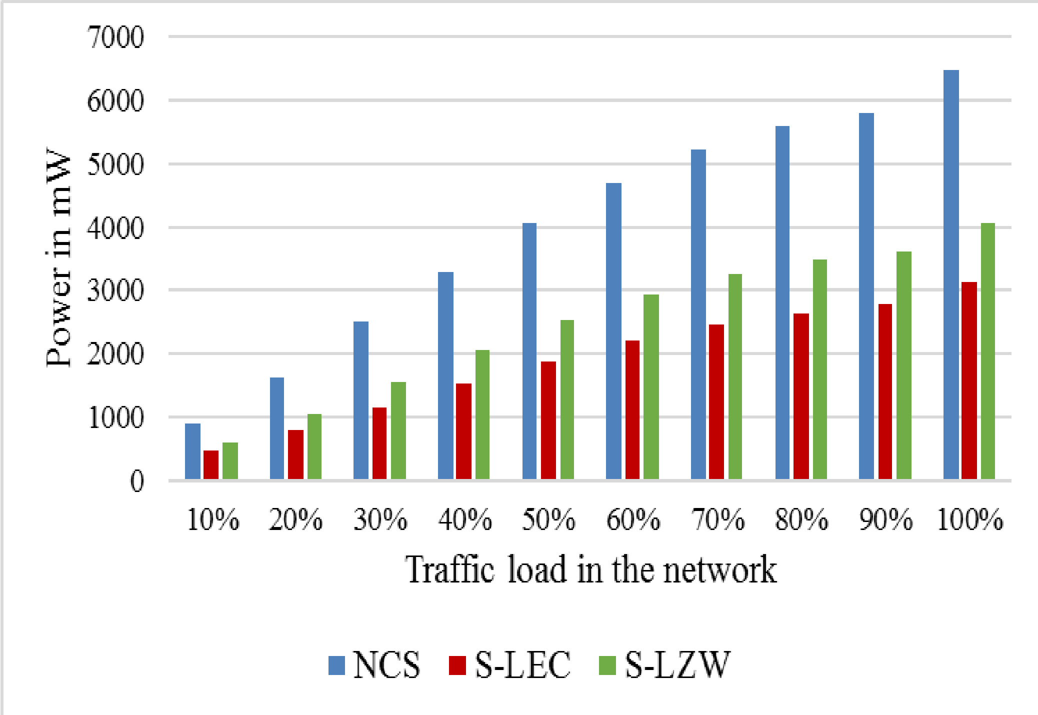


Figure 5-4: Total power consumption in the IoT network when the link bit rate is 500 kbps for each node: a) NCS; b) with the S-LZE compression algorithm; and c) with the S-LEC compression algorithm.

1)The results in Figure 5-4 display the total power consumption of the IoT network in mW, versus different percentages of the number of IoT devices that generate 500 kbps of bit rate for each device. The results display that there is an average power saving of 33% in the S-LZW compression algorithm and about 40% in the S-LEC compression algorithm compared to NCS, which is due to reducing the traffic of each link in addition to selecting efficient energy per bit and idle power IoT devices, as in (5.2).

2) The results in Figure 5-5 display the total power consumption of the network in mW, with 1000 kbps of bit rate for each device. They show that the network is fully working in NCS as long as the traffic load is below 60%. However, when it rises above this, the network goes down with NCS due to packet drops out and hence, data compression should be used to minimise the traffic. Additionally, the Auto scheme chooses S-LEC algorithm as the optimal selection since it minimises the transmission power more than other algorithms do.

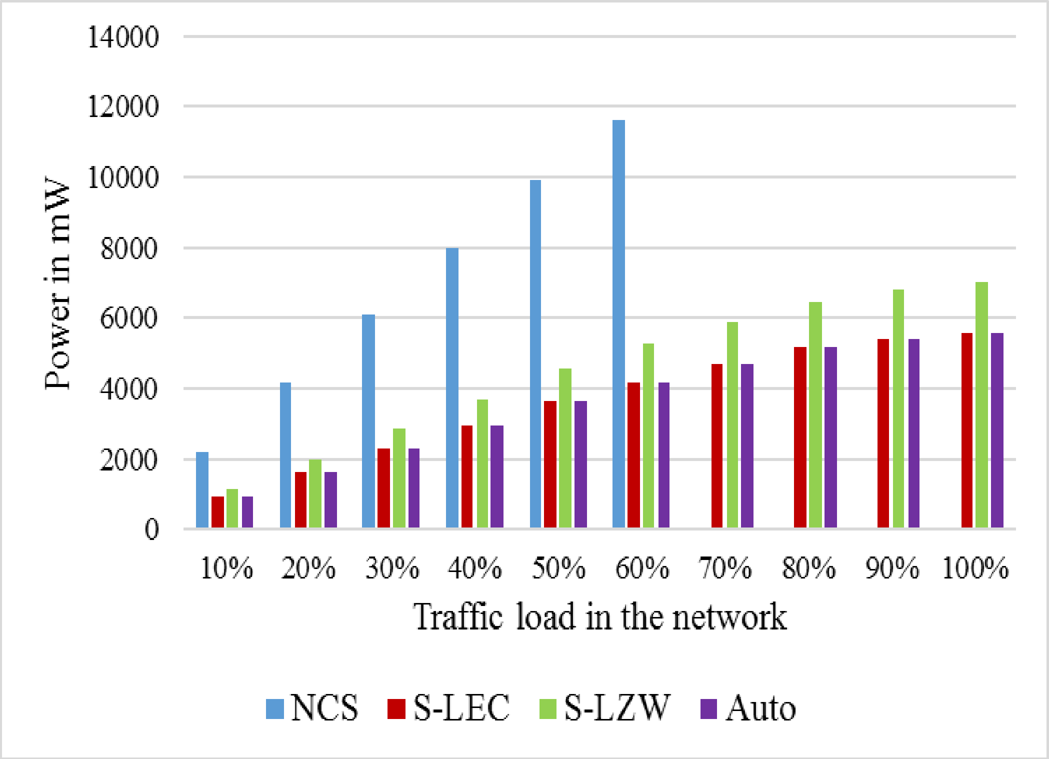


Figure 5-5: Total power consumption in the IoT network when the link bit rate is 1000 kbps for each node: a) NCS; b) with the S-LEC compression algorithm; c) with the S-LZE compression algorithm; and d) with Auto selection.

3) The results in Figure 5-6 display the number of hops in the network, with a bit rate of 1000 kbps for each node. They show that the number of hops in the NCS is higher, being almost 60 hops at 60% of traffic load. While in data compression schemes, the network does not need multiple routes and so it can use the same number of hops without breakdown the network.

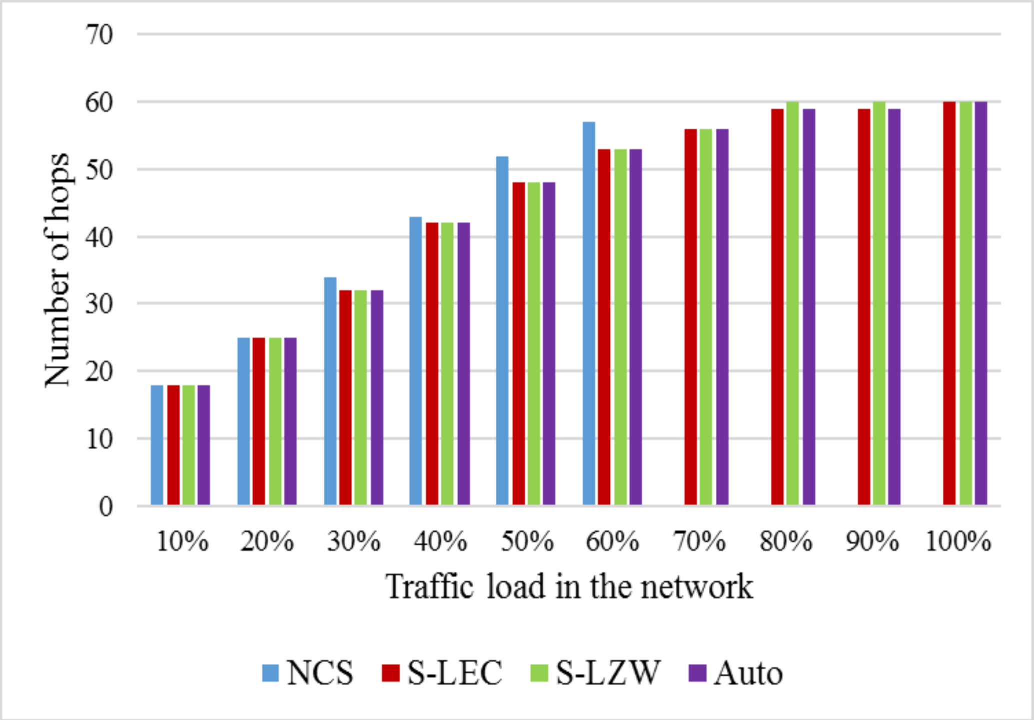


Figure 5-6: Total number of hops when the link bit rate is 1000 kbps for each node: a) NCS; b) with the S-LEC compression algorithm; c) with the S-LZE compression algorithm; and d) with Auto selection.

4) Figure 5-7 displays the number of sub-operations during the node lifetime with different traffic load in the network. The results show that the number of sub-operations decrease as the traffic load increases. Furthermore, in ADCS, the number of sub-operations increased to 50% compared to NCS.

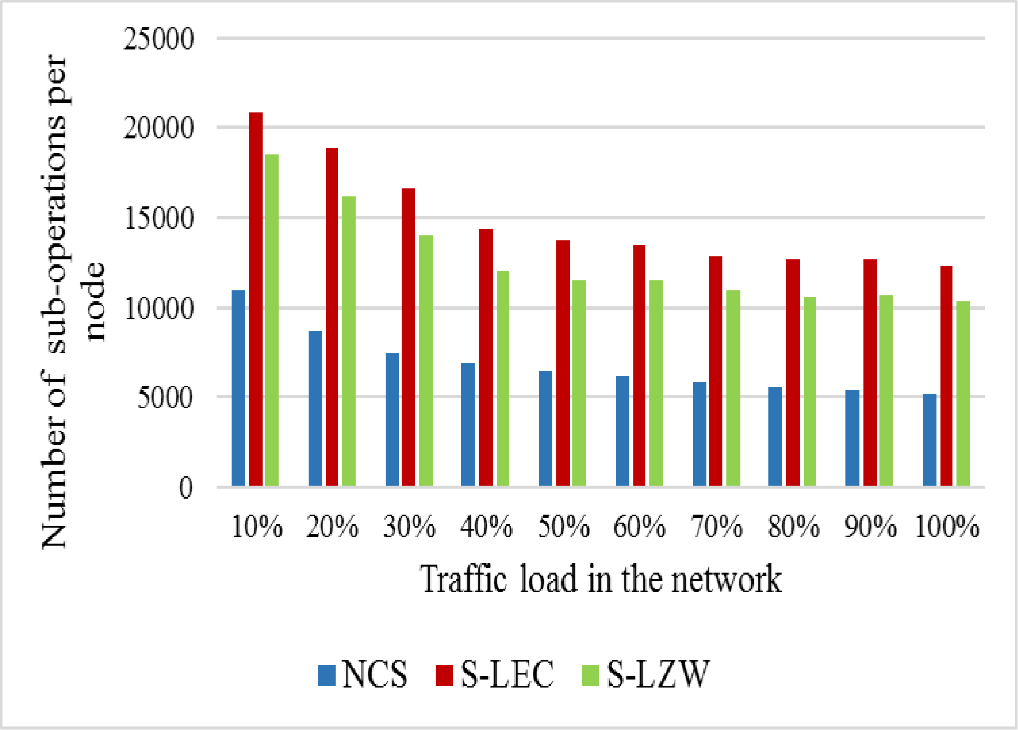


Figure 5-7**:** Number of sub-operations for each node when the link bit rate is 500 kbps for each node: a) NCS; b) with the S-LEC compression algorithm; and c) with the S-LZE compression algorithm.

Chapter 6

6 Conclusions, Future Work and Work Impact

6.1 Conclusions

In this thesis, a cloud based IoT system has been developed using the MILP model aiming at minimising the total transmission power consumption and achieving reliability. This thesis proposes a real-world scenario of smart buildings in a smart city with multiple user applications [126, 127, 145], with the user application performing in the cloud and requesting data collection. To achieves these aims, the following contributions have been proposed:

To improve the reliability of the IoT network, reducing transmitted power and mitigate interference, four schemes consisting of SBRS, DRLS, RBS and RBDS, have been proposed. Specifically, the standby routes selection scheme (SBRS) is used to selectively choose standby routes to overcome nodes failure problem and reduce transmission power. Also, the desired reliability level scheme (DRLS) is used when a specific reliability level is needed to guarantee the link reliability while minimising transmission power. Furthermore, reliability-based sub-channel scheme (RBS) uses sub-channel to mitigate interference and reduce overhead on links that utilised by several IoT devices due to its high reliability. Finally, reliability-based data compression scheme (RBDS) use sequential lossless entropy compression (S-LEC) data compression algorithm to overcome capacity limits of the links and reduce transmission power.

The results show that our proposed schemes have reduced the negative effect between reliability and total traffic power consumption with an average power saving of 57% in SBRS and 60% in RBDS compared to DRLS.

The routing of cloud based IoT is suggested to be used in the IoT network as a promising technology to minimise the total traffic power consumption by selecting the minimum number of hops between IoT devices and cloud. Other proposed schemes to minimise power consumption are the selectin of the energy efficient sub-channels by exploiting fading gain and utilising time slots of the energy efficient sub-channels and thus reducing interference through this sub-channel selection. The MILP model evaluates the results for two scenarios of optimisation:

1- Reducing the number of hops.

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 minimising hops and sub-channel selection when compared to just minimising the hops, as in the first scenario put forward.

Reduction of the transmission and computation power consumption, maximising of the network lifetime and enabling the utilisation of the network capacity is accomplished by developing an adaptive data compression scheme (ADCS) using a MILP model, ADCS includes S-LEC and S-LZW data compression schemes. ADCS in the Auto scheme can select the most energy efficient data compression scheme, while also considering the IoT device battery level (10% of total battery level), processing capability and compression power. The ADCS system was compared with a non-compression scheme, and the results showed that the ADCS provides an energy saving of 33% and 40% for S-LZW and SLEC, respectively, compared to NCS. That is a result of reducing the number of hops and the traffic load in the network; consequently, the system is able to handle a higher traffic demand, and this ability expands the IoT device lifetime (tasks cycles) by 50% compared to NCS system.

6.2 Future Work

6.2.1 Dynamic sink node allocation in cloud based IoT

In this research, the gateways, that collect the data from the sensors and/or actuators to send it to the cloud, are assumed distributed, i.e. there are several gateways have been distributed in multiple locations of the cloud based IoT network. In future work, it is suggested that the gateways to be dynamic and not fix, where it will be allocated according to the total consumed power of transmission in the network. The total traffic power consumption of a dynamic sink node allocation scheme would be compared with fix sink node scheme.

6.2.2 Distributed traffic

In this future work, it is suggested splitting the data traffic over two or more nodes to avoid link overhead, packet drop and latency. The nodes will be selected according to the available traffic and the link capacity limits. The total traffic power consumption results of two schemes, distributed traffic scheme and non-distributed traffic scheme would be compared.

6.2.3 Processing splitting

In this suggested future work, it is proposed that mandatory distributing the processing task to the nodes themselves instead of the cloud to reduce latency. The need for several nodes is due to the node's limited processing and storage ability. The model will compare the total power consumption of the IoT network for two scenarios of optimisation, first central processing in the cloud and second, distributed processing in the nodes of the IoT network.

6.2.4 State-of-the-art energy efficient data compression techniques

For future work, it is suggested to seek state-of-the-art energy efficient data compression techniques. Currently, data compression algorithms are suggested to be used in the IoT networks as a promising technology to minimise the traffic data, where these algorithms are reducing the amount of data to be transmitted and then reducing transmission power. There will be a comparison between two schemes 1- Non-compression scheme, 2- Data compression scheme to evaluate the energy efficiency for each scheme.

6.2.5 Intelligence in IoT networks

In this thesis the computing process is centralised in the cloud, therefore, as future work it is suggested using fog computing as a decentralised computing infrastructure in which data, compute, storage and applications are located somewhere between the data source and the cloud. Using the fog computing for data processing requires the IoT network to be intelligent, thus to decide on sending the collected data to the cloud or for fog computing. Artificial intelligence simulates intelligent behaviour in machines of all kinds; the model will calculate how much power has been consumed and saved for each case.

6.2.6 Practical Implementation

Deploying proposed work to a practical application. For example - using sensors in a manufactory, these sensors 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.

6.3 Work Impact

This section shows the positive impact of our work of energy efficiency and smart buildings on environment, health, energy and cost. Energy efficiency presents a critical factor that should be taken into considerations in the designation of the future internet, which integrate the internet of things. Two main reasons that would raise the importance of energy efficiency are:

- Economic advantage: saving money by reducing CAPEX and operational expenditure (OPEX), this can be attained by decreasing the costs expenditure by the operators to retain their network running at the improved QoS.
- Reducing pollution to the environment: reduction of global warming, wastes and emission of CO2.

Furthermore, smart city projects worldwide build on the advanced sensor, information, and communication technologies to help to deal with issues like air pollution, waste management, traffic optimisation, and energy efficiency.

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