

DUAL ENERGY MANAGEMENT AND ENERGY SAVING
MODEL FOR THE INTERNET OF THINGS (IOT) USING
SOLAR ENERGY HARVESTING (SEH)

by

Nasser Albalawi

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As members of the Dissertation Committee, we certify that we have read the dissertation prepared by: **Nasser Albalawi**
titled: **Dual Energy Management and Energy Saving Model for the Internet of Things (IoT) Using Solar Energy Harvesting (SEH)**

and recommend that it be accepted as fulfilling the dissertation requirement for the Degree of Doctor of Philosophy.

Jerzy W. Rozenblit

Jerzy W Rozenblit (Jan 6, 2024 22:30 EST)

Jerzy W Rozenblit

Date: Jan 6, 2024

Janet Meiling Roveda

Janet Meiling Roveda

Date: Jan 6, 2024

Pratik Satam

Pratik Satam (Jan 8, 2024 12:54 MST)

Pratik Satam

Date: Jan 8, 2024

Final approval and acceptance of this dissertation is contingent upon the candidate's submission of the final copies of the dissertation to the Graduate College.

I hereby certify that I have read this dissertation prepared under my direction and recommend that it be accepted as fulfilling the dissertation requirement.

Jerzy W. Rozenblit

Jerzy W Rozenblit (Jan 6, 2024 22:30 EST)

Jerzy W Rozenblit

Dissertation Committee Chair

Electrical and Computer Engineering

Date: Jan 6, 2024

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ABSTRACT

The *Internet of Things (IoT)* is a fast-growing internet technology and has been incorporated into a wide range of fields. The optimal design of IoT systems has several challenges. The energy consumption of the devices is one of these IoT challenges, particularly for open-air IoT applications. The major energy consumption takes place due to inefficient medium access and routing, which can be addressed by the energy-efficient clustering method. In addition, the energy harvesting method can also play a major role in increasing the overall lifetime of the network. Therefore, in the proposed work, a novel energy-efficient dual energy management and saving model is proposed to manage the energy consumption of IoT networks. This model is based on dual technologies, i.e., energy-efficient clustering and solar energy harvesting (SEH). The proposed method is implemented for high-density sensor network applications. The dual elbow method is used for efficient clustering and guaranteed QoS. The model is able to manage energy consumption and increase the IoT network's overall lifetime by optimizing IoT devices' energy consumption. The protocol was simulated in MATLAB and compared to Fuzzy C-Means (FCM) and Time Division Multiple Access scheduling (TDMA) based Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol, based on network lifetime.

CHAPTER 1

Introduction

The Internet of Things is collectively known as an interconnected network of various devices and sensors, each with unique attributes[8]. According to the study, around 80 billion devices will be deployed worldwide by the year 2025[4]. IoT facilitates seamless interaction across all sectors by providing real-time data analysis, monitoring, and predictive analytics[13]. IoT enhances productivity and improves quality of life. With all the various aspects, it also faces some challenges, such as security, resource optimization, and power consumption[37].

1.1 Definition of IoT

The phrase Internet of Things (IoT) was first used by Kevin Ashton in 1999 [17] as a field where physical objects are connected to the Internet through sensors and a network [22]. The term has an extensively comprehensive meaning that can be applied to diverse sectors such as commerce, industrial, operational, domestic, and infrastructure domains [19]. IoT is defined by the author [22] as a vast and inclusive network of intelligent objects with the capacity to share data, self-organize it, and respond to environmental changes. According to study [29], IoT is defined into three basic categories: Machine-to-machine communication (M2M). People to Machines

or people to things and People to People communication via the internet. Hence, the IoT, in a comprehensive perspective, is defined as the devices connected via an internet connection and capable of sharing data and communicating with each other [35].

1.2 IoT Components and Resources

The IoT consists of various components and resources that work in collaboration with each other to gather and process data.[19],[35]. These components and resources are explained as follows:

- **Sensors and Actuators:** This category includes diverse sensor nodes, from basic home appliances to complex industrial machines. These interoperable components record data and signals such as temperature, humidity, motion, and other readings generated[19].
- **Gateways and Network:** IoT is supported by a robust network structure that includes gateways, data acquisition systems, and several wired and wireless communication technologies, including Ethernet, Wi-Fi, GSM, ZigBee, and Bluetooth. Together with sensors and actuators, these components efficiently gather and optimize the massive amount of produced data for processing [6].
- **Distributed Computing Infrastructure:** This framework includes edge computing, cloud servers, and big data analytics. It effectively processes streaming

data using open architectures as well as distributed computing. It utilizes machine learning abilities, which offer features like data integration and visualization and provide accurate feedback for improved IoT system performance [14].

- **Power Supply and Energy Source:** IoT devices often operate in places with limited access to charging and power supply. As these devices and sensors need constant power sources for seamless data processing and gathering to ensure the efficiency of an IoT device, power supply options are crucial, such as expanding battery capacity or exploring alternative energy sources [32].
- **Security and privacy:** One important component of the IoT ecosystem is the security and privacy of the data gathered by IoT nodes. Various authentication mechanisms and security protocols are included in this category to ensure data integrity, security, and reliability [21].

These components and resources work together to develop a better and scalable IoT infrastructure and model for better results and performance.

1.3 IoT Architecture

IoT architecture refers to the framework or structure specifying how various Internet of Things components connect and interact [17]. As there is no universally agreed upon architecture for IoTs various researchers have proposed different architectures

[35].

1.3.1 Three-Layered and Five-Layered Architectures

The simplest and basic architecture is discussed in the study [35], which comprises three layers which include:

- Perception Layer: The layer includes sensors, actuators, fog nodes, and devices that are responsible for collecting data from the physical world [5]. These devices and sensors can collect signals and data from various entities and objects. The data is transmitted to the next layer for processing. It is basically the physical layer with the sensors and devices [35].
- Network Layer: This layer is responsible for the communication between devices and the cloud network. It processes the data transmitted from the perception layer and utilizes various communication protocols such as HTTP/HTTPS / IPv6, etc. [35].
- Application Layer: This layer provides a diverse range of applications to the users [35]. The top layer caters to various IoT applications, such as smart homes, healthcare, logistics, transportation, energy management, and media applications. The layer provides the ground where IoT devices are deployed practically [17].

In addition to the basic three-layer architecture, the five-layer architecture has

additional processing and business layers.

- **Processing Layer:** The middleware and analytical layers provide an abstraction between the upper and lower layers. It serves as a link between the top and bottom layers and lies between the physical layer and the application layer [35]. It controls device connectivity, saves data, processes information, and provides various services using technologies like databases, cloud computing, and big data processing [17].
- **Business Layer:** This layer is responsible for the tracking and management of the whole IoT system, which includes various applications, industrial models, and user data and privacy. It performs business intelligence analysis on the data transmitted from the application layer to improve its effectiveness further. IoT applications are integrated into business processes and corporate systems by the business layer [35].

1.3.2 IoTWF Standardized Architecture

A Standardized Architecture for IoT was released by the IoT World Forum (IoTWF) in 2014. This architecture comprises a seven-layer reference model where endpoint devices are controlled by the center entity, which is typically the cloud. Most of the time, data is gathered at these endpoint devices and transferred to the central processing point [13]. The decentralized central processing can also be implemented as a cloud service. The layers can be stated in the study [13] as :

- Layer of Things/device layer has actuators and sensors.
- The connectivity layer has the responsibility of analyzing and cleaning the data from devices and transmission to the upper layers
- The edge layer is responsible for aggregating and processing data to mitigate the lags that occur because of heavy data flow. The layer provides the facility to analyze the data closer to the device where the data is originally created to enhance the processing efficiency.
- The Data storage layer prepares data for database storage and makes sure that regardless of the data format, it can be retrieved via queries later.
- The Data aggregation layer makes sure that data is consistent and validated for reliable queries and retrieval.
- The Application or analytical layer is responsible for making sure that the respective application can perform various functions on the data, such as reporting, analyzing, and visual processing.
- The Collaboration layer serves the purpose of the business layer to perform intelligent analysis to extract the key benefits and advantages from the data shared for enhanced efficiency in the future.

The three- and five-layer architectures provide a basic understanding of the Internet of Things but are insufficient for an in-depth IoT study [35]. Although it

provides a baseline knowledge, IoT research usually focuses on deeper and more complex aspects of this developing industry. A more thorough approach is required to address these complexities adequately; therefore, a more layered architecture was introduced to provide scalability and interoperability [13].

1.4 Application of IoT and Associated Problems

IoT has the potential to revolutionize all domains, such as health care, smart cities, logistics, transportation, agriculture, and businesses. Various Application domains with the usage of IoT are discussed as follows:

1.4.1 Industrial IoT

Industrial IoT and the concept of Industry 4.0 improve productive operations by applying internet technology with a focus on data security and computation, data storage, and information processing. In industrial automotive settings, the IoT can enable predictive maintenance for M2M and asset tracking for process optimization [25].

1.4.2 IoT in Health and Agriculture

In agriculture, the application of IoT helps in addressing population growth and climate change by monitoring crops and optimizing resource use of water and soil. With the help of intelligent trash cans and effective collection of waste material, it

encourages a safe environment and economic support in recycling and waste management. IoT improves health care through remote monitoring of patients and early symptom identification, improving patient safety [25].

1.4.3 Smart Cities, Power and Transportation

IoT addresses the challenges of urbanization through smart cities by improving the quality of life for the citizens. It enables effective resource management and enhances security through intelligent community monitoring. By implementing intelligent utility metering and power distribution, IoT optimizes grid management. The concept of the Internet of Vehicles, which includes the intelligent driving system, has transformed the automobile experience [25]. The sensor nodes connected to various applications and objects collect, process, and transmit the data. Apart from the latency and cyber security issues [3], the power consumption in sensor nodes remains a significant challenge [36].

1.5 Resource Management and Power Consumption Challenges

Effective energy management is essential for IoT devices because of the hardware and design challenges related to power consumption. Many IoT devices must function autonomously for extended periods of time, which often depends on batteries. These difficulties cover a number of areas, including sensing and data transmission from various external resources [32]. They are used to collect and send environ-

mental data. Device processing is another energy-intensive operation as IoT devices struggle to handle real-time data within resource limits. The installation of IoT devices in harsh environments or extreme conditions may put extra pressure on power sources [17]. The enormous amount and speed at which IoT devices generate data have a substantial influence on battery life and total power consumption, requiring innovative approaches for sustainable operation [36].

1.6 Power Consumption in IoT

Power consumption in the Internet of Things (IoT) refers to the amount of electrical energy consumed by IoT devices when they operate [1]. For several reasons, power consumption is a critical consideration for IoT designers and developers. IoT devices do not have direct power supply access because of their size and resource constraints. Another main reason behind this is the placement of IoT devices in locations where electrical network supply is nearly impossible. Thus, they often rely on batteries as their primary power source. However, excessive power consumption can result in shorter battery life. This is especially crucial for devices meant to operate for extended periods without human intervention in remote locations.

1.6.1 Energy Cost in IoT

Continuous operations of IoT devices have a significant impact on the cost of energy in IoT [10]. These operations include:

- **Data Collection** Many IoT devices have sensors to collect data. For example, a smart thermostat monitors ambient temperature. It requires power each time it collects data. The more frequently it samples or the more sensors it has, the greater the energy consumption.
- **Data Transmission** Transmitting data typically consumes more power than just collecting it. For example, a weather station that sends updates to the cloud every minute will consume more energy than one that sends updates every hour.
- **Data Receiving** IoT devices also need to receive data, such as configuration commands, software updates, or other forms of input. While this might not be as frequent as sending data, it still contributes to the device's overall energy consumption.
- **Data Processing** IoT devices often process the data locally before transmission, apart from sending and receiving data. This processing can range from simple tasks like data filtering to more complex operations, such as image recognition in smart cameras.
- **Connectivity** The cost of energy also depends on the type of connectivity used by IoT devices. For example, Wi-Fi generally consumes more power than other low-power communication protocols like ZigBee or Lora WAN [23]. Moreover, the energy cost can vary based on the distance data needs to travel,

the frequency of communication, and the chosen protocol.

1.6.2 Importance of Energy Consumption Management in IoT

Energy consumption in IoT holds vital importance. A significant portion of IoT devices are battery-powered and deployed in areas where frequent manual recharging or battery replacement is either impractical or costly. Efficient power consumption ensures longer device lifespans and reduced frequency of maintenance. Ultimately, it results as minimizing operational costs. Moreover, cumulative power usage can be substantial as the number of IoT devices increases globally. Therefore, energy efficiency in IoT is essential for both environmental and economic reasons. Efficiently powered IoT devices contribute to versatility and ease of deployment in various applications due to their compact design. Last but not least, the reliability and consistency of IoT systems largely depend on stable energy sources. Fluctuations or inconsistencies in power supply can lead to data loss, reduced device performance, or system failures in some extreme circumstances. Hence, power efficiency directly impacts the reliability, scalability, and sustainability of IoT ecosystems [41].

1.6.3 Handling of Energy Consumption in IoT: State of the Art

Low power consumption ways and energy handling techniques didn't come inherently with IoT. Simply stated, efficient energy handling can be the difference between a device functioning for years versus just days or weeks. Various energy consumption

handling techniques can be found in the existing literature. The following briefly describes some prominent techniques and state-of-the-art for effectively handling energy consumption in IoT.

- **Duty Cycling** The concept of duty cycling in IoT devices is based on “don’t need to be continuously active” [25]. Instead, IoT devices can alternate between active states, where they perform tasks like sensing or communicating, and sleep or low-power states, where most of the device’s functions are minimized or turned off. Thus, the proportion of time a device spends in its active state versus its sleep state determines its duty cycle [26]. For example, if an IoT device is active for 1 minute and then sleeps for 9 minutes, its duty cycle can be denoted as:

A lower duty cycle typically means better energy efficiency because the device spends less of its time in the more energy-consuming active state. However, the optimal duty cycle depends on the specific application and requirements of the IoT device. For example, a heart rate monitor might need a higher duty cycle than a soil moisture sensor. This is because monitoring heart rates requires more frequent readings than monitoring soil moisture.

- **Adaptive Sampling and Transmission** in IoT devices highlight a responsive approach to energy management [2]. Traditional IoT devices sample data at fixed intervals regardless of the environment or the nature of the data. On

the other hand, adaptive sampling adjusts the frequency of data collection based on specific criteria or conditions. For example, a temperature sensor might sample more frequently when temperatures rapidly change and less often when stable. Like adaptive sampling, adaptive transmission adjusts the frequency and volume of data transmission based on various factors. A device might send data only when a certain threshold is reached or adjust the transmission rate based on network congestion and available bandwidth[2]. This dynamic behavior ensures relevance and timeliness in the data captured and significantly reduces energy wastage to enable longer operational lifespans of IoT devices and optimized network usage.

- Edge Computing represents a paradigm shift in data processing for the IoT ecosystem [24]. Traditional IoT devices primarily act as data collection points and send their raw data to centralized servers for analysis. However, with edge computing, a considerable portion of this data processing occurs directly on the IoT device or "at the edge" [23]. This local processing of data at the edge significantly reduces the volume of data that needs to be transmitted over the network and ultimately leads to noticeable energy savings, especially given that data transmission often consumes more power than local processing. Moreover, processing data locally can lead to quicker decision-making. Hence, this localized processing becomes particularly relevant for IoT in bandwidth constraints and latency sensitivity scenarios. Thus, edge computing not only

presents a power-efficient alternative but also enhances the responsiveness and autonomy of IoT devices.

- **Artificial Intelligence and Machine Learning** Machine learning algorithms are being employed to predict and manage device behavior to minimize energy consumption. Various researchers proposed machine learning and artificial intelligence-based strategies to cope with the energy consumption problem in IoT. For example, the authors introduce a day-ahead dynamic pricing model designed to optimize energy demand response strategies for IoT [24]. This model aims to reduce peak-time demand and lower electricity tariffs for end-users. For effective implementation, the authors emphasize the importance of a smart grid system having insights into future short-term power consumption and renewable energy outputs. The authors determined that real-time monitoring and control over electricity consumption and renewable energy generation become feasible by integrating their model at a weather monitoring station with IoT devices [5].
- **Energy Harvesting** As its name suggests, energy harvesting refers to capturing and storing small amounts of energy from external sources and then using this energy to power electronic devices [39]. As described earlier, IoT devices operate in diverse environments, often far from conventional power sources. So, the primary challenge associated with those remotely deployed IoT devices is

to ensure that they remain operational for extended periods without frequent battery replacements or recharging. Thus, energy harvesting emerges as a vital solution to sustain prolonged device operation because it offers a sustainable solution by utilizing energy from the surroundings of the devices. IoT devices not only use the energy in real-time, they also store the harvested energy for a continuous power supply during the unavailability of the energy harvesting source. Modern IoT devices can incorporate multiple energy harvesting methods by using algorithms to switch between them based on environmental conditions [30]. For example, an outdoor IoT sensor might mainly rely on solar harvesting during the day and switch to vibration or RF energy harvesting at night [30]. There are different types of energy harvesting, such as Solar Harvesting, Thermoelectric Harvesting, Vibration Energy Harvesting, Wind and Fluid Flow Harvesting, and RF Energy Harvesting. However, Solar is a widely used source for energy harvesting in IoT environments [40].

- Solar Energy Harvesting As described earlier, solar is one of the most common forms of energy harvesting [40]. Solar harvesting leverages the ample energy of sunlight. Photovoltaic (PV) cell is at the heart of solar harvesting. PV cell is a semiconductor device that can convert sunlight into direct current (DC) electricity [11]. When photons from sunlight hit the PV cell, they excite electrons and create an electric current. That electric current can be used to power the IoT device and even store the energy to use it at night time. The

following figure represents a high-level overview of solar energy harvesting.

One of the advantages of solar harvesting for IoT is its scalability. While large solar panels can power homes or businesses, smaller, flexible solar cells can be integrated into IoT devices [28]. These miniature panels can be tailored to fit various shapes and sizes, making them adaptable to various devices. Thus, solar harvesting is ideal for remote IoT devices where regular battery replacement or grid-based charging is impractical. For example, weather sensors in remote locations, agricultural sensors in large farms, or even wearable devices regularly exposed to ambient light

1.7 Energy Consumption in IoT: Analysis of Gaps

The first and foremost challenge for energy consumption management in IoT is that most IoT devices have made advances in energy efficiency through hardware optimization [38]. However, there's an evident lack of unified standards and protocols that can universally guide the development and operation of these devices. This fragmentation often leads to devices operating sub-optimally and consuming more energy than necessary due to incompatible communication standards or unoptimized software algorithms. Moreover, integrating renewable energy sources and energy harvesting techniques with IoT devices is still emerging. Solar or vibration energy harvesting is used in some situations, but it has not caught on much yet because of problems with storage and cost [43]. A consistent framework for integrating

and managing these renewable sources with IoT devices is noticeably absent. As IoT ecosystems grow, there is a pressing need for universal solutions that address immediate energy consumption and pave the way for future sustainable and resilient energy management.

1.8 Motivation

The rapid proliferation of the Internet of Things (IoT) has led to the integration of diverse devices, presenting numerous opportunities and challenges. One of the critical challenges is the energy consumption of IoT devices, particularly in heterogeneous networks where various devices with distinct characteristics coexist. The motivation behind the present work lies in addressing this challenge by proposing an energy-efficient routing and clustering protocol tailored for heterogeneous IoT networks. While existing variants of LEACH have aimed at energy-efficient data transmission, there remains a trade-off between energy consumption and throughput. The motivation here is to develop a method that not only reduces energy consumption but also enhances throughput, crucial for maintaining a balance between competing quality of service parameters.

In addition, the proposal recognizes the significance of optimal design in IoT systems, emphasizing the need to manage energy consumption effectively. Open-air IoT applications, in particular, face challenges related to inefficient medium access and routing, contributing significantly to energy drain. The motivation for the

second part of the work is to introduce a novel dual energy management and saving model, incorporating energy-efficient clustering and solar energy harvesting. This dual approach seeks to address the energy consumption challenge and extend the overall lifetime of the IoT network. The proposal is particularly motivated by the potential impact of these energy-efficient methodologies on diverse sensor network applications, promising advancements in both energy conservation and quality of service.

1.9 Contribution

This dissertation makes the following main contributions:

- The proposed work introduces a dual energy management model that combines energy harvesting techniques with a novel clustering routing approach. This model allows the network to harvest energy from the environment, such as solar energy, to power the network operations energy-efficiently.
- The proposed idea focuses on energy-efficient clustering in IoT networks. The proposed work integrates energy harvesting methods into the clustering process to optimize energy utilization and prolong the network lifetime.
- By integrating energy harvesting with clustering and routing approaches, the proposed work aims to improve the network's overall efficiency. Energy harvesting provides an additional energy source, reducing the reliance on battery

power and enhancing the network's resilience and sustainability.

- Energy harvesting techniques can help replenish the energy resources of the network, reducing the frequency of battery replacements or recharging. This extended network lifetime can be a significant advantage, particularly in remote or inaccessible areas where frequent maintenance is challenging.
- The proposed work holds potential for real-world implementation as energy harvesting techniques are increasingly being explored and utilized in IoT deployments. The proposed work can enhance practical and energy-efficient IoT networks by integrating these techniques with existing research methods.

1.10 Problem Statement

The battery is the primary power source for most IoT open-air applications, and the life of the battery is limited. Due to the difficulty of replacement and the amount of time required, employing merely a battery is insufficient, even if using multiple or larger batteries to extend the device's lifespan. Also, changing batteries frequently in many remote locations is nearly impossible. Inadequate energy will result in poor performance, data loss, etc. Therefore, alternate energy sources are required to power IoT nodes continuously. As these devices continue to work, machines need a sufficient power supply to keep them alive. By default, open-air devices' primary power source will be batteries, as shown in Figure 1.1. As is known to all, each IoT

thermore, the battery's lifetime is uncertain, making it difficult to estimate when to replace it.

Addressing this issue, energy harvesting (EH) technology is a promising solution for achieving energy self-sufficiency. EH offers alternative energy sources that can be harnessed across various open-air applications, ultimately extending the operational lifespan of batteries. The EH aims to convert various forms of ambient environmental energy, such as heat, light, airflow, vibrations, electromagnetic waves, and other phenomena, to electrical energy to supply a low-power electronics system entirely or partially [45]. The IoT node power sources have been classified into three main categories, as illustrated in Figures 1.2. In the proposed work, the IoT devices are conceptualized to integrate with batteries and energy harvesting sources [12]. The proposed work deals with combining two primary power sources for the IoT. A rechargeable battery is used for energy storage, and a solar panel is used for harvesting. A power management consumption model is developed and designed using battery and harvesting techniques such as solar panels, which will extend the battery's lifespan for an extended period of time. In addition, system resources are managed by maximizing their operation, dependent on the available energy.

1.11 Dissertation Structure

The rest of the dissertation is organized as follows: We conducted a literature survey and discussed the related work in Chapter 2. An overview of the energy management

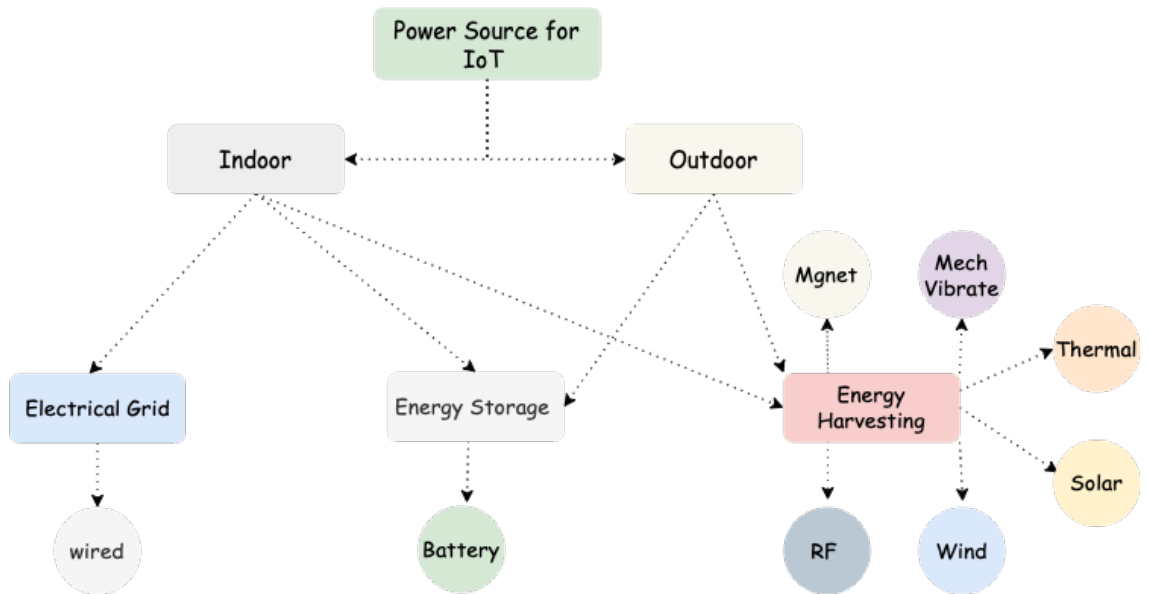


Figure 1.2: Overview of the various power sources for IoT node

model is elaborated in Chapter 3. In Chapter 4, we elaborated on experimental evaluation.

CHAPTER 2

Related Work

One of the biggest challenges is managing the energy of the IoT node in terms of prolonging its lifetime. Numerous techniques exist for employing solar energy harvesting as an alternative energy source to power the IoT node. Also, various research works are reported related to the efficient clustering and optimal allotment of the transmission medium.

The authors [34] presented a clustering protocol that aims to increase the lifetime of sensor nodes by taking three levels of energy heterogeneity into account, and the cluster head is chosen in such a way that the cluster formed by the head contains a greater number of high-energy nodes. One potential constraint of this approach pertains to the finite lifespan of sensor nodes, primarily attributed to their reliance on smaller battery capacities. Additionally, the overall longevity of the network is diminished when energy conservation measures are not effectively implemented.

Zandhessami et al. [46] The energy constraint in sensor-based IoT networks, combined with the lack of rechargeability in most applications, necessitates utilizing computational intelligence techniques in designing and implementing algorithms. This significantly aids in reducing energy consumption and ultimately prolonging the network's lifespan.

S. Hriez et al. [15] proposed a clustering protocol for wireless sensor networks in mission-critical IoT scenarios, addressing energy limitations and trustworthiness concerns. The protocol extends the network's life using stochastic fractal search optimization and a trust model that finds nodes that cannot be trusted based on energy and data trust. The author has analyzed the performance experimentally to prove the superiority of the proposed method. The author has used a trust model. However, guaranteed throughput is not ensured for efficient clustering.

R. Ramya et al.[31] introduce a novel approach known as Things Network LEACH (TN-LEACH) with the objective of enhancing network performance by reducing packet delay time, prolonging network lifespan, and extending data transmission duration. However, a potential limitation of this study is battery life, as the model continues to rely on the battery as its primary power source.

The improved LEACH protocol is introduced by Jain et al.[18] as a hierarchical protocol with a cluster head selection algorithm and cache node selection to make it easier for data to move from the sensor node to the sink node. The cluster head nodes need to transfer data to cache nodes, which are selected in terms of the closest physical distance. This approach significantly increases processing power, memory usage, and network bandwidth, which might lead to more power consumption.

Rahil Bensaid et al. [7] propose a new Fuzzy C-Means (FCM)-based clustering algorithm for energy efficiency in Wireless Sensor Network (WSN)-based Internet of Things (IoT) systems, which increases network lifetime by 50% by increasing

residual energy. However, the limitation of this study is the battery's lifetime, as the model still relies on it as the primary energy source.

A.J William et al. [44] Equitable cluster heads (CHs) distribution is paramount for increasing network lifetime and ensuring continuous observation coverage. A novel two-fold approach, second-fold clustering (SFC), is proposed. In the initial phase, CHs are selected based on zonal residual energy and zonal degree of connectivity. Subsequently, the remaining isolated nodes are grouped in the second phase, selecting CHs based on zonal connectivity to achieve near-uniform energy distribution across nodes.

Researchers have done a lot of work on efficient routing and clustering. Still, as far as we know, they have not done any work on combining best practices for energy harvesting and guaranteed throughput with efficient clustering and optimal slot allocation. The proposed work proposes energy-efficient clustering with an optimal slot allotment method for guaranteed QoS. In addition, the integrated energy harvesting method is used to improve lifespan.

This paper displays the widespread use of solar energy harvesting in IoT applications. The objective was to review the technologies used in this harvesting system. The authors highlight techniques that improve energy conversion efficiency, such as DC-DC converters, charge pumps, and MPPT (maximum power point tracking). This type of harvesting is already widely implemented in IoT applications, indicating its practical significance. The review finds that the charge pumps greatly improve

voltage gain discreteness and conversion ratio matching, increasing the harvester's efficiency. The evolution of technologies like MPPT indicates the continuous development of the efficiency of the harvester. The reconfigurable charge pumps enhance energy conversion efficiency [20].

This paper examines the rapid growth of IoT and the demand for low-powered wireless sensors. Reviewing energy harvesting advances and presenting case studies. Explains the importance of low-power wireless sensors. These sensors are applicable in various fields such as transportation, energy, infrastructure, healthcare, environment, monitoring, defense, manufacturing, and production. It emphasizes the need for long-term, self-sustaining IoT device design and implementation. According to the paper, battery-powered sensors have drawbacks in system cost, network performance, and lifespan. Harvesting ambient energy can extend sensor life. Eliminate battery power, green the environment, and increase network maintenance costs. Finally, these case studies demonstrate that energy harvesting is feasible in real-life IoT scenarios[33].

CHAPTER 3

Energy Management Model Overview

3.1 Mathematical Model

The dual-energy management system is proposed to prolong the lifetime of the IoT network, as shown in Fig 3.1. The solar energy harvesting method delivers extra energy for real-time operations. The section is divided into subsections for the mathematical modeling of different phases and operations.

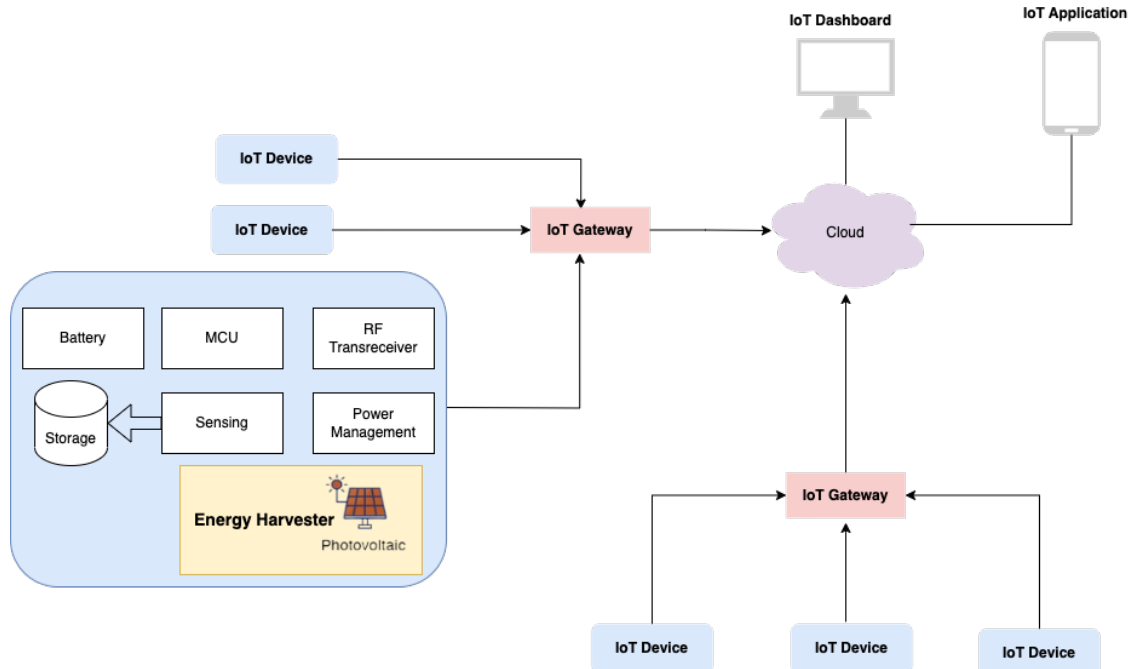


Figure 3.1: Architecture of a typical energy-harvesting IoT node

3.1.1 Network Parameters

Let us assume an IoT network. The following list includes the typical IoT network parameters used in IoT simulation, with some modifications based on the implementation.

- N is the number of nodes in the network.
- E_i be the energy level of node i .
- E_{opti} is the optimal energy level by optimal data slot prediction and sleep mode adjustment of node i .
- E_{Savi} is the overall energy saving of node i .
- P_i be the power consumed by node i for data transmission.
- H_i be the solar energy harvesting rate of node i .
- T be the time duration for data transmission.
- C_i be the cluster assignment of node i in the setup phase.
- M is the number of clusters formed in the setup phase.
- M_{opt} is the number of optimal clusters formed in the setup phase.
- D_i be the data traffic generated by node i in the steady state.
- D_{sn} is the time slot allotted to sensor node i in the steady state.

- D_{ch} is the time slot allotted to cluster head node i in the steady state.
- S_i be the sleep time duration of node i in the steady state.
- λ_i be the predicted data traffic rate of node i .
- μ be the energy conversion efficiency of the energy harvesting system.
- α is the energy consumption coefficient for data transmission.
- p is the traffic generation probability for each node.

3.1.2 Optimal Clustering

In the setup phase, we apply a clustering approach to divide the network into optimal clusters (M_{opt}) to enhance energy efficiency. Each node i calculates the distance to other nodes and selects the closest node as the cluster head. The cluster head communicates with its associated nodes.

Let us assume the cluster is divided into M clusters optimized to the optimal clusters (M_{opt}) using the proposed two-fold elbow method. The optimal number of clusters is estimated based on the two-fold Elbow method. Instead of the traditional method, the proposed work determines the two elbows for efficient optimal clustering. It involves calculating the within-cluster sum of squares (WSS) for different values of M .

Let C_i represent the i -th cluster, and C_i^* be the centroid of the i -th cluster. Then, the WSS for each cluster is calculated as the sum of squared distances between each

data point x_j and its cluster centroid C_i^* , where j iterates over all data points in cluster C_i :

$$WSS = \sum_{i=1}^M \sum_{x_j \in C_i} \|x_j - C_i^*\|^2 \quad (3.1)$$

The total WSS for all M clusters is the sum of individual WSS values:

$$\text{Total WSS} = \sum_{i=1}^M WSS \quad (3.2)$$

The two nearby elbows are estimated based on WSS values to estimate an optimal number of clusters (M_{opt}). Let us assume, based on the WSS graph, M_{Elbow1} is the elbow corresponding to the minimum value of WSS, and M_{Elbow2} is the next nearby elbow of M_{Elbow1} .

$$M_{opt} = \frac{M_{Elbow1} + M_{Elbow2}}{2} \quad (3.3)$$

3.1.3 Energy-Efficient Optimal Mapping TDMA (EEOM-TDMA) Approach in the Steady State

We adopt the EEOM-TDMA approach to optimize data transmission in a steady state. Each cluster node allows data transmission using the TDMA protocol, while the bit mapping-based optimal mapping technique ensures interference-free data transmission.

The power consumed during steady-state data transmission, i.e., P_i for the cluster head device and the sensor node device, can be given as follows:

Cluster Head Device

The cluster head device consumes power for both data transmission and reception, as given below:

$$P_{\text{ch}} = \alpha \cdot D_{\text{ch}} + \alpha \cdot D_{\text{recv}} \quad (3.4)$$

where D_{ch} is the data traffic generated by the cluster head, and D_{recv} is the data traffic received from the associated sensor nodes.

Sensor Node Device

The sensor node device only consumes power for data transmission to the cluster head:

$$P_{\text{sn}} = \alpha \cdot D_{\text{sn}} \quad (3.5)$$

where D_{sn} is the data slot allotted for data traffic generated by the sensor node.

3.1.4 Sleep Mode Approach for Data Traffic Prediction

To save energy, nodes implement a sleep mode approach by predicting future data traffic λ_i and adjusting their sleep time S_i accordingly. A hybrid prediction method is used for the prediction-based optimal slot allotment. The slots are allotted based on classification-cum-regression (*CcR*) method. The random forest method is used

to deal with dynamic data traffic conditions for the optimal slot allotment. The predicted data traffic of i^{th} node is estimated based on the training of the previously generated data traffic as given below:

$$\lambda_i = CcR[Avg(\sum_{i=1}^{N-1} D_i)] \quad (3.6)$$

3.1.5 Power Consumption Model

The energy consumption of node i in the steady state can be modeled without sleep mode optimization as follows:

$$P_i = \begin{cases} \alpha \cdot (D_{ch} + D_i) & \text{if node } i \text{ is the cluster head} \\ \alpha \cdot D_i & \text{if node } i \text{ is a sensor node} \end{cases} \quad (3.7)$$

The power consumption (P_{opti}) of node i in the steady state can be modeled with sleep mode optimization as follows:

$$P_{opti} = \begin{cases} \alpha \cdot (D_{ch} + \lambda_i) & \text{if node } i \text{ is the cluster head} \\ \alpha \cdot \lambda_i & \text{if node } i \text{ is a sensor node} \end{cases} \quad (3.8)$$

The energy harvested by node i during the time T is given by:

$$H_i = \mu \cdot T \quad (3.9)$$

The energy balance equation for node i without optimal sleep mode is:

$$E_i = E_i^0 + H_i - P_i \cdot T \quad (3.10)$$

where E_i^0 is the initial energy level of node i .

The energy balance equation for node i with optimal sleep mode is:

$$E_{opti} = E_i^0 + H_i - P_{opti} \cdot T \quad (3.11)$$

The energy saving due to optimal sleep mode can be derived as follows:

$$\begin{aligned} E_{Savi} &= E_{opti} - E_i \\ &= (P_i - P_{opti}) \cdot T \\ &= P_i \cdot \sum S_i \end{aligned} \quad (3.12)$$

The sleep duration can be estimated as,

$$S_i = D_i - \lambda_i \quad (3.13)$$

3.1.6 Traffic Generation Probability

The data traffic generated by each node follows a probabilistic model. Let D_i be the data traffic generated by node i in the steady state. The data traffic can be expressed as follows:

$$D_i = p \cdot D_{avg} \quad (3.14)$$

where D_{avg} is the average data traffic generated by all nodes.

In the case of sleep mode optimization, the data traffic generated by each node is represented by λ_i by node i in the steady state. The data traffic can be expressed as follows:

$$\lambda_i = p \cdot \lambda_{\text{avg}} \quad (3.15)$$

Where λ_{avg} is the average data traffic generated by all nodes in case of sleep mode optimization.

3.1.7 Lifetime Comparison

To compare the network's lifetime with and without energy harvesting, we can use the concept of average energy consumption per unit of time. Let L be the lifetime of the network.

For the network without energy harvesting:

$$L_{\text{no harvesting}} = \frac{\sum_{i=1}^N E_i^0}{\sum_{i=1}^N \alpha \cdot (p \cdot D_{\text{avg}})} \quad (3.16)$$

For the network with energy harvesting:

$$L_{\text{harvesting}} = \frac{\sum_{i=1}^N (E_i^0 + \mu \cdot T)}{\sum_{i=1}^N \alpha \cdot (p \cdot D_{\text{avg}})} \quad (3.17)$$

For the network with energy harvesting and optimal slot allotment:

$$L_{\text{harvesting}} = \frac{\sum_{i=1}^N (E_i^0 + \mu \cdot T)}{\sum_{i=1}^N \alpha \cdot (p \cdot \lambda_{\text{avg}})} \quad (3.18)$$

CHAPTER 4

Experimental Evaluation

A simulation of the Internet of Things nodes (IoT) for a proposed protocol with customized parameters is taken into consideration. The proposed protocol was simulated in a MATLAB environment. The major objective of the simulation work in this section is to evaluate energy consumption and network lifetime across various scenarios.

4.1 Simulation Parameters

The simulation area dimensions, base station location, number of nodes, election probability, packet lengths, energy capacities, and propagation constants are defined in Table 4.1. The simulation loop iterates through rounds, selects cluster heads based on probabilities, and calculates energy usage for data transmission. The network's total energy consumption and lifetime are computed, accounting for standard (reduce function device) and advanced nodes (fully function device). The results are analyzed to compare and interpret the trade-offs between energy consumption and network longevity. This simulation offers a deeper understanding of the proposed protocol's behavior under various conditions and can aid in optimizing energy-efficient designs for wireless sensor networks.

Table 4.1: Simulation Parameters

Parameter	Description
Simulation Area	$x = 200m, y = 200m$
Base Station	$(100m, 100m)$
Number of Nodes	$numNodes = [50, 100, 150, 200, 250, 300]$
Election Probability	$p = 0.05$
Packet Lengths	$packetLength = 500Bytes$
Energy Capacities	$Battery = 1800mAh, Harvester = 200mAh$
Initial Energy	$Eo = 0.5J$
Energy Constants	$ETX = 50nJ, ERX = 50nJ$ $Efs = 10nJ, Emp = 0.0013nJ$
Data Aggregation	$EDA = 5nJ$
Maximum Rounds	$R = 2000$

4.2 Result

The result section is analyzed for six different scenarios. The number of nodes is varied from 50 nodes to 300 nodes, as shown in Fig 4.1 to Fig 4.6. The two essential results are presented to analyze energy consumption and the network's lifetime. Various features are integrated for efficient clustering and medium access for the overall reduction of energy consumption. In addition, the two-elbow method is used to ensure optimal throughput. The energy harvesting method is also integrated with the network architecture to improve a lifetime.

The energy consumption is analyzed for varying nodes. The nodes are varied from 50 to 300 Nodes. Fig 4.7 The deployment of nodes, including the cluster head, cluster node, and cluster, is crystal clear with the utilization of different colors that make it easier to understand and implement the system efficiently.

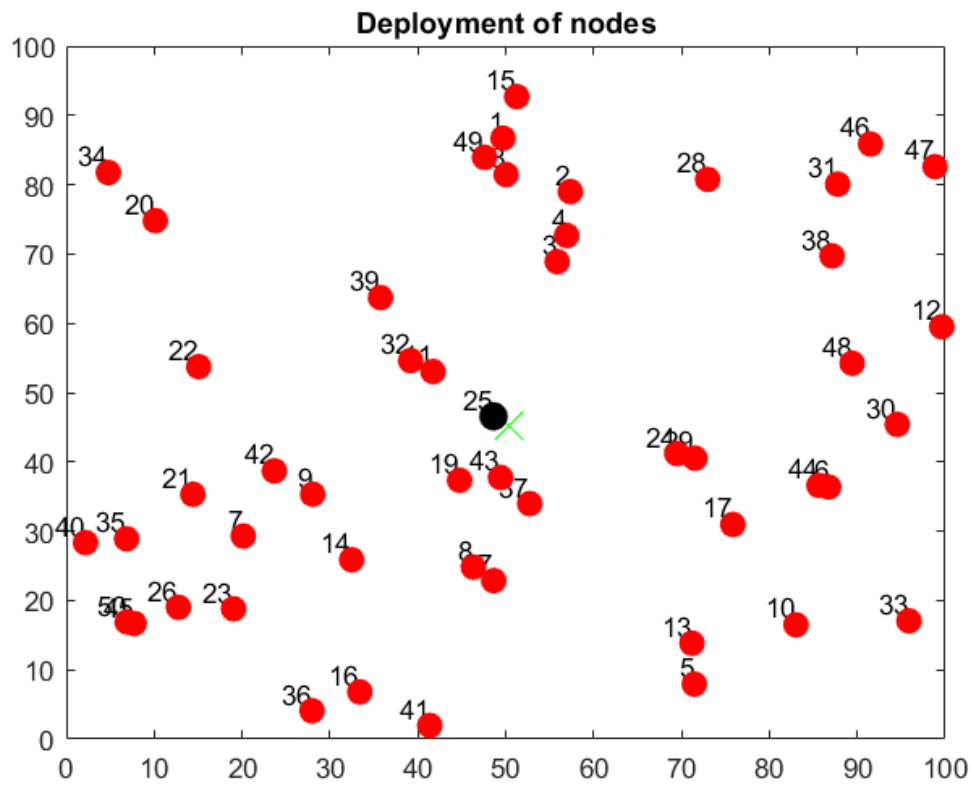


Figure 4.1: Deployment of 50 Nodes

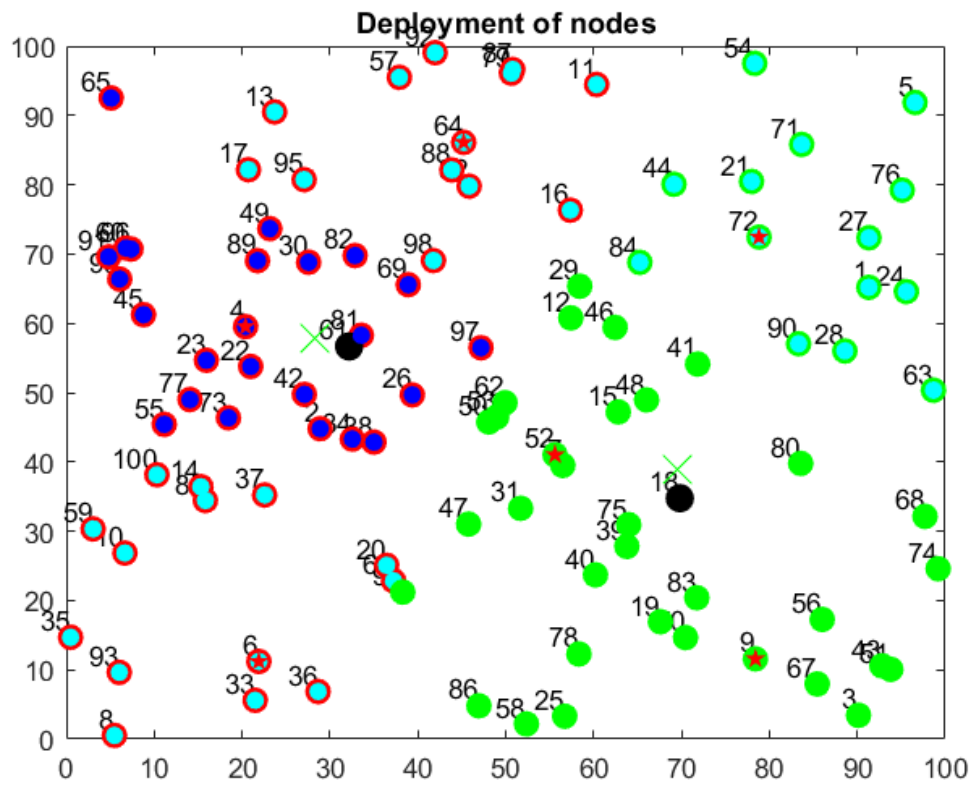


Figure 4.2: Deployment of 100 Nodes

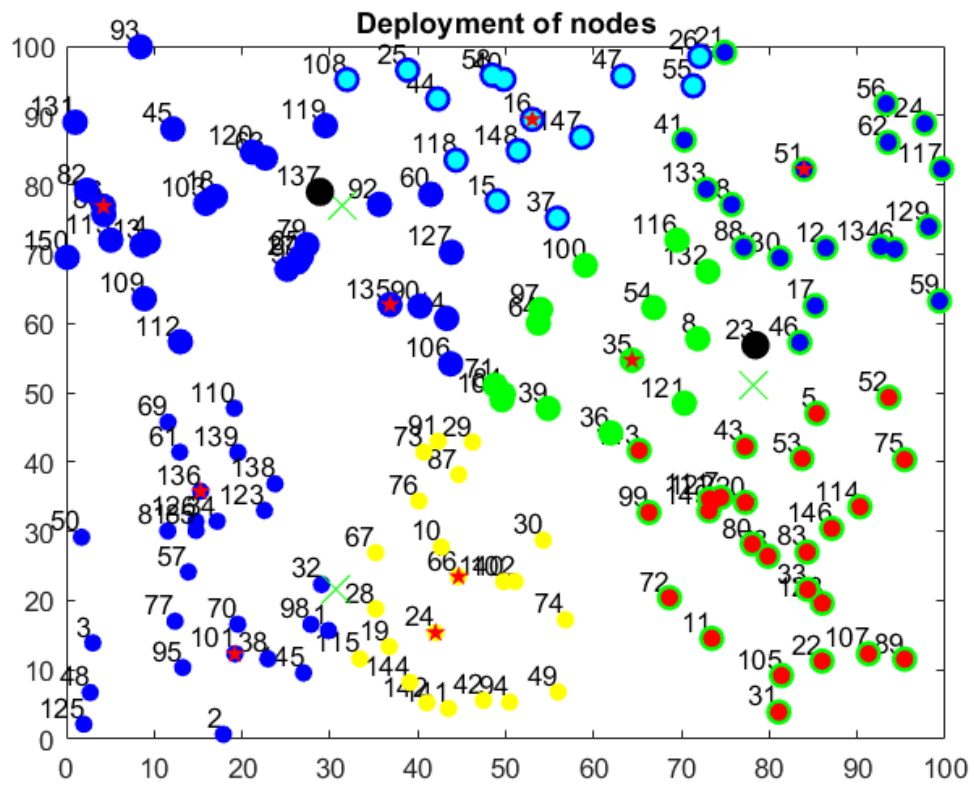


Figure 4.3: Deployment of 150 Nodes

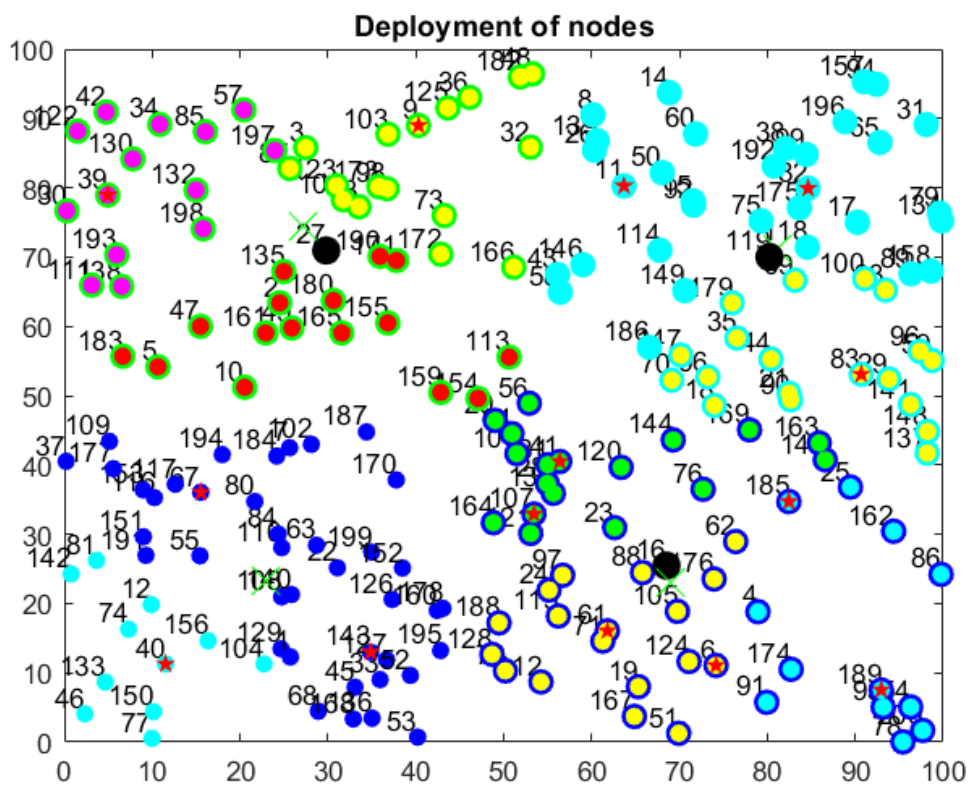


Figure 4.4: Deployment of 200 Nodes

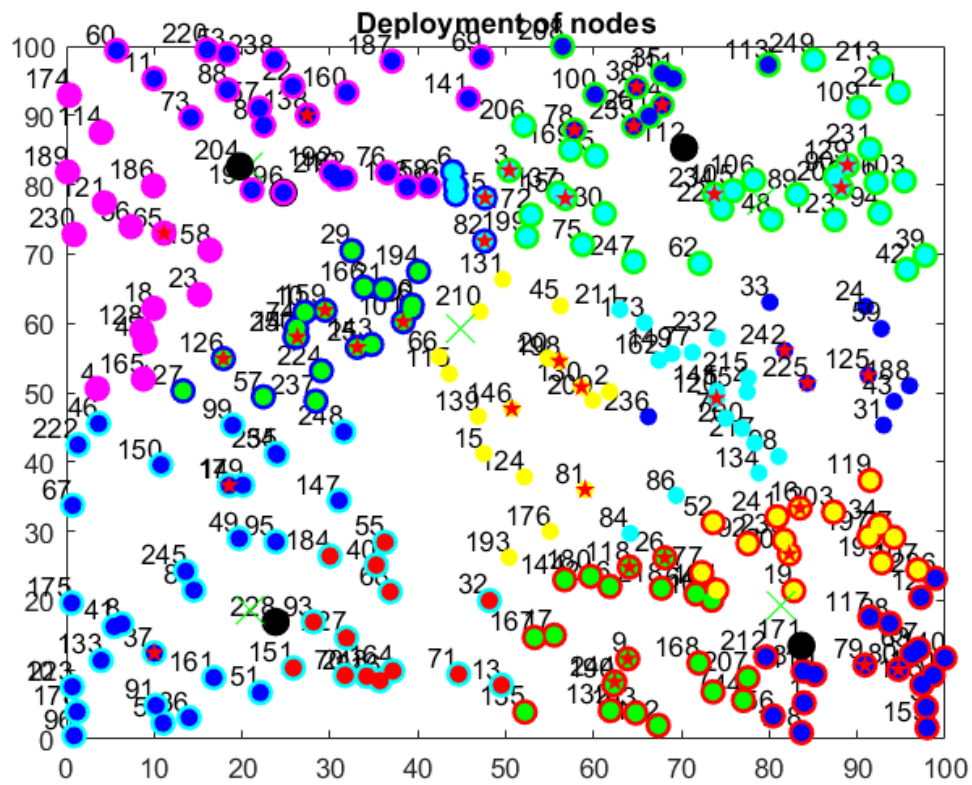


Figure 4.5: Deployment of 250 Nodes

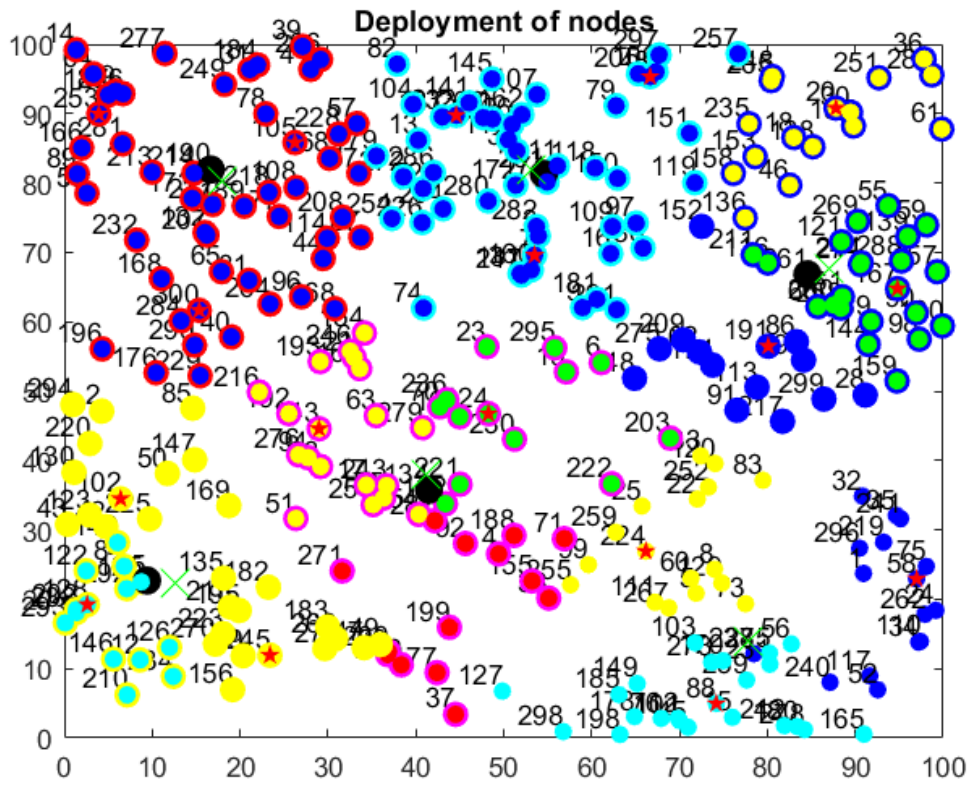


Figure 4.6: Deployment of 300 Nodes

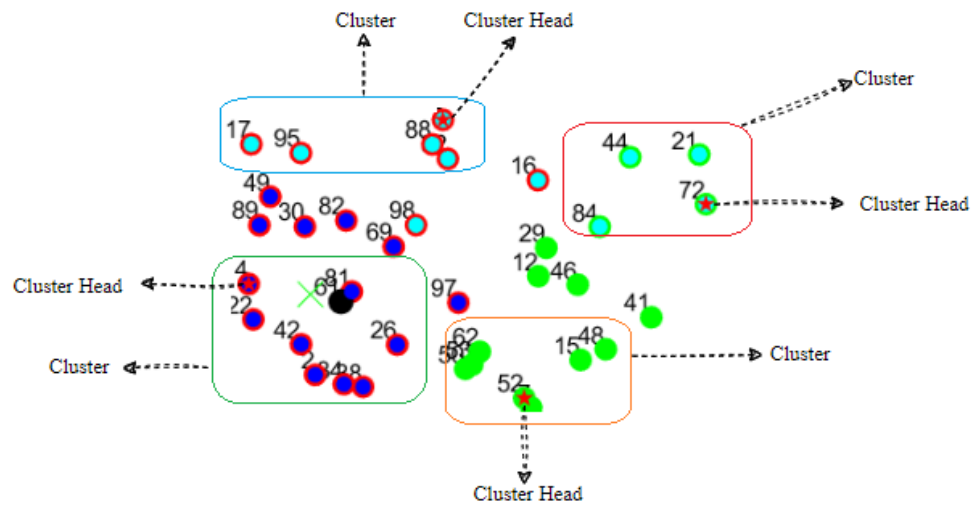


Figure 4.7: Part of Nodes deployment for explanation

Table 4.2: Node Power Consumption for Around

Number of Nodes	Total Energy Consumption
Number of Nodes: 50	17.03 <i>Joules</i>
Number of Nodes: 100	38.11 <i>Joules</i>
Number of Nodes: 150	57.11 <i>Joules</i>
Number of Nodes: 200	70.09 <i>Joules</i>
Number of Nodes: 250	92.44 <i>Joules</i>
Number of Nodes: 300	106.72 <i>Joules</i>

Table 4.2 displays the estimated total power consumption associated with each round in IoT nodes. The network performance is analyzed with respect to the existing methods. The performance of the proposed method is compared with FCM and TDMA-based LEACH methods. Both methods are developed for the performance analysis of IoT networks. As shown in Fig 4.8, the energy consumption of the proposed IoT method is lower than the other protocols. This is because the proposed protocol checks the buffer in the allotted time slot and goes to sleep mode instead of idle mode in case of an empty buffer. In addition, the proposed method efficiently allots the time slots and uses a two-elbow method for optimal throughput.

To further check, the overall lifetime of the network performance is analyzed with the integration of an energy harvesting system. The results show a significant improvement in the overall lifetime (approx. 20%) of the network performance, as shown in Fig 4.9.

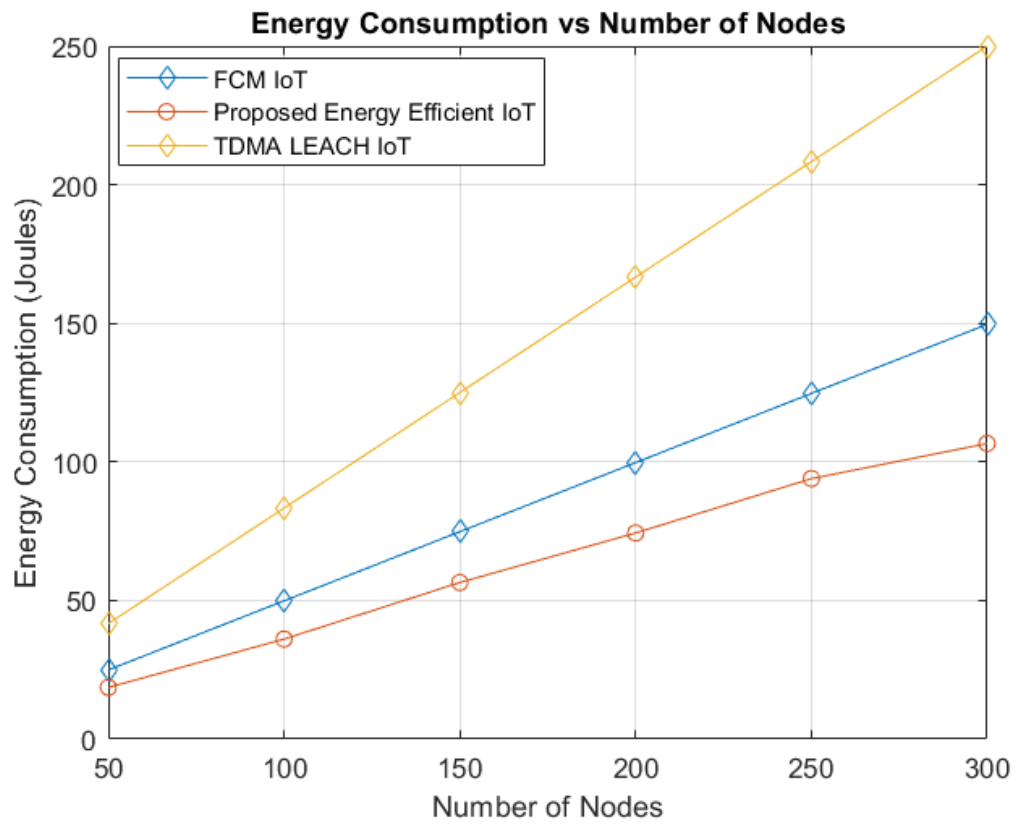


Figure 4.8: Comparative Analysis of Energy Consumption

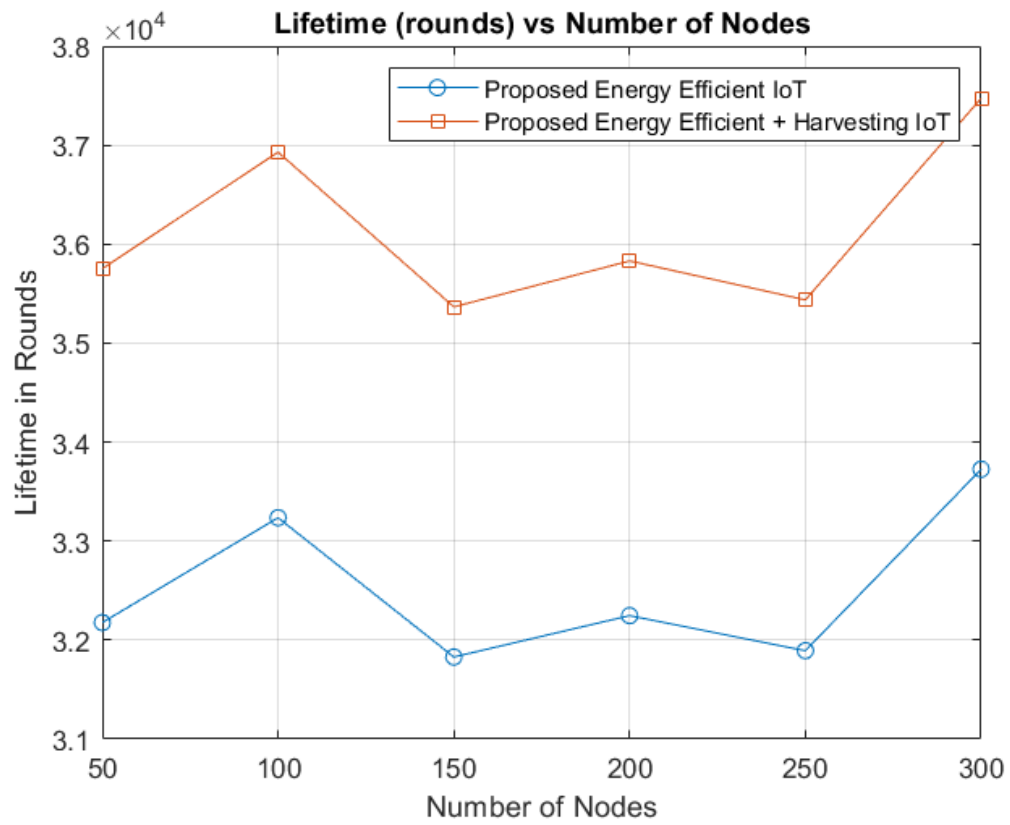


Figure 4.9: Comparative Analysis of Lifetime of the Network

CHAPTER 5

Conclusion and Future Work

5.1 Conclusion

This dissertation presented a model for an IoT network with longevity for open-air applications. A novel approach has been proposed to address energy consumption challenges in IoT systems by developing a dual energy management model that combines energy-efficient clustering with the integration of the energy harvesting method. The model aims to optimize energy consumption, extend network lifetime, and enhance overall efficiency. The results show the significance of energy harvesting in IoT deployments and the contribution of clustering and routing. They also indicate improved energy consumption and network lifetime through comparisons with existing protocols. The results show that the overall energy consumption is reduced by approximately 25% and an overall lifetime increase of 20%. The results prove the overall utility of the proposed method.

5.2 Future Work

More research in this area aims to find new ways to make energy use more efficient. For example, one idea is to make an energy prediction model that can achieve en-

energy neutrality and ensure sensor nodes work reliably based on when energy will be available. Additionally, we should consider incorporating the TinyML model into the sensor node's firmware. As our model uses the homogeneous approach, we should also consider the development of heterogeneous nodes with different hardware, software, communication capabilities, or energy levels compared to other nodes in the network. Clearly, this work is only a simulation-modeling-based foundation for implementing energy-efficient IoT networks. We believe that it can have significant utility in many practical applications, for example, agriculture or weather tracking.

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